New technology and old institutions: An empirical analysis of the skill-biased demand for older workers in Europe

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Abstract

Using panel data from nine European countries over the period 1970 to 2007, we examine the impact of information and communication technology (ICT) on the demand for older workers (aged 50 and over). We find evidence of a decrease in demand for older workers in the 1970s and 1980s. It can be argued that the impact of ICT on demand for older workers is skill-biased. However, the skill-biased demand for older workers is mainly reflected in the skill-biased changes in employment shares rather than relative wages. There is some evidence of a gradual deskilling of older workers. We find that labour market institutions such as the national minimum wage, social pacts on wage issues and union density mostly benefit skilled older workers, while coordination of wage setting, extension of collective agreements, social pacts on pensions and centralisation of wage bargaining can alleviate the adverse effects of skill-biased technological change.

JEL Classifications: J21, J24, J31

Key Words: Earnings, Older workers, Information and Communication Technology, Labour Market Institutions

1. Introduction

A number of existing studies have attempted to identify the determinants of the skilled-unskilled wage premium. Some studies have focused on the role of technology or skill-biased technological change (SBTC), especially the impact of information communication technology (ICT) (e.g., see Acemoglu, 1998 and Mallick and Sousa, 2017).[1] Using firm and industry level data, it has been argued that improvements in ICT have allowed highly skilled workers to earn higher wages (e.g., see Autor et al., 1998).[2] Skill, or educational attainment, is only one dimension of worker characteristics that influence their ability to adapt to new technology. Other dimensions include gender and age. However, few studies have focused on these aspects. Exceptions include Card and Lemieux (2001) who argue that the well-known increase in the skill premium for college-educated workers in the US in the 1980s was concentrated in younger age cohorts and could be attributed to a low supply of graduates relative to previous cohorts. In a more recent study, Daveri and Maliranta (2007) consider the links amongst age, seniority, wages and information technology.[3]

The focus of this paper is on the age dimension, in particular, the demand for workers aged 50 and over in Europe. We discuss the complementarities between human capital and technology, where technology is represented by capital accumulation in the form of ICT. Human capital theory (Becker, 1964; Mincer, 1974) suggests that the decision to invest in human capital is based on cost-benefit considerations for both employers and employees. In relation to new technology, human capital theory predicts that lower levels of learning ability contribute to lower productivity in the workplace. It is generally believed that learning ability declines after a certain age and it can therefore be argued that the effectiveness of human capital investment (in terms of the potential gains to the employer from higher productivity and the worker from higher earnings) declines with age. This is likely to lead to both lower offers of human capital investment in older workers and less incentive for them to accept any offers

[1] The literature on the determinants of skilled-unskilled wage inequality is rapidly growing. Some recent empirical studies have started to focus on the role of non-market factors. For example, using data on 43 US industries from 1968 to 2012, Kristal and Cohen (2016) argue that a decline in unionization and the real value of the minimum wage can also account for a significant proportion of skilled-unskilled wage inequality in the US. Other related studies, such as Kawaguchi and Mori (2014), aim to explain rising wage inequality by focusing on supply side factors. Using micro data from some European countries, Garnero et al. (2014) examine the impact of the minimum wage and collective bargaining on wage inequality.

[2] In a very interesting recent study, using decomposition techniques, Marouani and Nilsson (2016) provide evidence of skill-biased technological change in Malaysia in recent years.

[3] Messinis and Ahmed (2013) use a new measure of human capital that also takes education, cognitive skill, life expectancy and the use of ICT into account.

that come their way (O'Mahony and Peng, 2009; Carmichael and Ercolani, 2014).[4] Caselli (1999) shows that a biased technology revolution affects wage inequality if the workforce is heterogeneous in training cost. Lower levels of learning ability may also raise the cost of human capital investment in older workers, in terms of time and effort, which could have an additional negative impact on the motivation to invest in such human capital. Hence, human capital investment (training) theory suggests a negative relationship between the demand for labour for older workers and new technology.

While this paper focuses on the impact of ICT on demand for older workers in some European countries, related studies have also considered the more general issue of the interactions between technology (especially ICT), efficiency, employment and skills. For example, using panel data for the UK manufacturing sector over the 1976-1982 period, Van Reenen (1997) finds that technological innovation has a positive impact on employment. A similar positive link between innovation (usually measured by R&D spending) and employment is found by Piva and Vivarelli (2005) and Hall et al. (2008) in Italy, Lachenmaier and Rottmann (2011) in Germany, Mitra and Jha (2015) in India, and Ciriaci et al. (2016) in Spain. Disaggregated studies that deal with the impact of technology on employment produced mixed results. For example, while focusing on the UK, Greenhalgh et al. (2001) find that the positive impact of R&D on employment was limited to high-tech industries. However, Lachenmaier and Rottmann (2011) did not find any significant sectoral heterogeneity between high-tech and non-high-tech sectors. Using time series data on 677 European companies over the 1990-2008 period, Bogliacino et al. (2012) find that the job creation effect of R&D spending was present only in the services and high-tech manufacturing sectors.

Technology affects employment though process and product innovation. It is generally believed that process innovation has a negative effect on employment whereas product innovation is basically labour-friendly (Brouwer et al., 1993; Smolny, 1998). Using data from France, Germany, Spain and the UK over the 1998-2000 period, Harrison et al. (2014) found evidence of process innovation as well as product innovation effect on employment. However, Hall et al. (2008) and Lachenmaier and Rottmann (2011) failed to find the employment displacement effect of process innovation. Even though most new technologies are labour saving, improvement in technology has not resulted in large scale unemployment.

[4] It can also be argued that older workers will have fewer years left in the workforce and that makes learning new skills less attractive both to them and to employers. At the same time, older workers, due to their accumulated experience, can remain highly productive. However, without learning new skills, at some stage, experience would not be able to offset the lack of knowledge of new technology. Other related studies include Pianta (2005), Frey and Osborne, and Brynjolfsson and McAfee (2014).

The initial labour-saving effect of process innovation can be counterbalanced by market compensation forces via new machines, new investments, decrease in prices and wages, and increase in income (Vivarelli, 2014). The possible labour-friendly impact of product innovation can also mitigate the negative effect of new technology on employment (Vivarelli and Pianta, 2000). The empirical evidence presented by Evangelista and Vezzani (2012) suggests that both technological and organizational innovation exert a positive impact on employment mainly by improving growth performances of the firms. They also find evidence of diminishing relevance of the labour displacing effect of the process innovation. Thus, the existing literature tends to support a positive link between new technology and employment, especially when R&D and/or production innovation are used as proxies for technological change and when high-tech sector become the focus of the study.

In some sectors, such as microelectronics and telecommunications where technology is skilled labour-friendly, improvement in ICT can be considered as product innovation. However, in the case of the manufacturing and services sector, improvement in ICT can be viewed as labour saving process innovation. The relationship between the ICT and employment is considerably more complex. The combined effect of process and product innovation can vary considerably across countries and sectors.

While the early studies focused on the quantitative aspect of the link between technology on employment, recent studies also consider the qualitative aspects in term of SBTC (Vivarelli, 2014). Several studies have reported that ICT and R&D investments contribute positively to the productivity and efficiency of firms (Acemoglu, 2015; Bonanno, 2016). The SBTC has shifted the demand for labour in favour of skilled workers thereby increasing the employment opportunities and wages of skilled workers (Acemoglu and Autor, 2011). At the same time, the past few decades have witnessed a rapid (and simultaneous) growth in both the highest- and lowest-skilled job. This phenomenon, which is also referred to as job polarization, is evident in the US (e.g., see Autor and Dorn, 2013; and Autor, 2015), the UK (e.g., see Goos and Manning, 2007), Germany (e.g., Spitz-Oener 2006; Dustmann et al., 2009) and Sweden (e.g., Adermon and Gustavsson, 2015). Goos et al. (2014) and Michael et al. (2014) find that the high- and low-paying occupations have expanded relative to middle-wage occupations in most European countries, suggesting that job polarization is pervasive across advanced economies.

The main explanation for the observed job polarization is that the new technologies are mainly designed towards replacing labour in routine tasks (Routine-biased technological change, RBTC) thereby decreasing the demand for middle-skilled “routine” cognitive and manual jobs. Workers with non-routine tasks lie at the two opposite ends of the skill distribution. For example, the professional speciality and manual personal services (Autor and Dorn, 2013).

In this paper, we attempt to test whether new technologies (especially the ICT) are complementary or substitute to the use of older workers within an industry. The SBTC hypothesis implies that employment (and therefore the earnings) of older workers decline as new technologies become available. However, the RBTC hypothesis highlights the advantages of older workers over the current technology. Older workers tend to have well developed job-specific abilities that help them apply the ICT to deal with non-routine tasks requiring situational adaptability and in-person interactions (Autor and Dorn, 2009). Accordingly, the older workers may gain employment in low-skill non-routine occupations within an industry.

It is commonly believed that learning ability deteriorates with age. However, the evidence is mixed (e.g., see Waldman and Avolio, 1986 and Wooden et al., 2001). If the new technology developed is codified in a standard way, then the lower learning ability of older workers might not be viewed as a serious obstacle to investment in human capital. The existing literature also suggests that different stages in the diffusion of technology can affect the demand for skilled workers. In some respects, ICT capital appears to become less complementary with skilled (or younger) workers over time. Chun (2003) argues for the need to distinguish between the short-run adoption effect that ICT has on the demand for skills and the long-run use effect, which may be considered as the "real" change in skill bias. Chun's analysis implies that, as new technology is fully implemented, firms can replace high-wage, highly educated workers with lower-paid older workers who are not highly educated. Ruiz-Arranz (2004) provides evidence of a decreasing contribution of ICT capital-skill complementarity to the growth of the skill premium in the US since the 1980s. More recent studies on job polarization, for example Michaels et al. (2014) and Goos et al. (2014), argue that ICT has led to an increase in demand for highly educated workers at the expense of middle-educated workers but demand for low-educated workers has scarcely been affected. Thus, a deskilling effect may replace the skill-biased demand for older workers at the late stage of the adoption process of new technology.

This paper investigates the impact of ICT on the demand for various types of workers (including a split by gender, three education groups and age) by using EU-KLEMS data.[5] We contribute to the existing literature in a number of ways. First, we estimate wage bill share equations for nine European Union (EU) countries: Austria, Belgium, Denmark, Finland,

[5] See Timmer et al. (2007a and b), http://www.euklems.net/

Germany, Italy, the Netherlands, Spain and the UK, using a uniquely diverse and disaggregated dataset involving 11 industry groups over the period 1970-2007. The dataset includes the service sectors as well as manufacturing. These sectors have been significantly affected by ICT (O'Mahony and van Ark, 2003). Thus, we are able to investigate the effect of skill-biased technology broken down by gender, age and education.

Second, a key feature of this paper is the consideration of the extent to which the impact of ICT on the demand for older workers is a long-term or merely a transient effect.[6] The use of industry data with a longer time span allows one to develop a deeper understanding of the evolution of technology over time and its impact on wage inequality. If, in the long run, technology is deskilling, we expect to see a gradual shift in the demand for older workers as ICT knowledge becomes more codified and accessible. The difference in the timing of the diffusion and adoption effects between countries is also considered by testing for structural differences in the estimated coefficients over time.

Third, we also considered the impact of labour market institutions on the wage shares of older workers. Vivarelli and Pianta (2000) and Vivarelli (2014) argue that the historical and institutional circumstances (e.g., social safety nets, reduction in working hours, union strategies and labour market flexibility) can have a significant impact on the dynamic relationship between new technologies and employment. Institutional setting can also mitigate the hindrances to compensation mechanism and alleviate the negative effect of new technologies on employment, especially for older workers. Countries may adopt and utilise technologies differently, depending on their institutional regulatory structure and absorptive capacity in relation to the availability of new technology (Acemoglu, 1998; Lewis 2011). The rigidity of labour market institutions and employment protection have been offered as explanations for the persistently higher unemployment rate and lower skill premium in Continental Europe (Peng and Siebert 2008; Anger, 2011; Afonso, 2016). On the other hand, institutions responsible for relative wage rigidity in continental Europe also encourage investment in technology that increases the productivity of less skilled or older workers, thus implying relatively less skill-biased technological change in these countries compared to the US (Acemoglu, 2003).[7] Thus, we need estimate the impact of these labour market institutions with a long history on the wage shares of older workers.

[6] The age groups used in this paper are defined as follows: 15-29 is young workers, 30-49 is senior workers and 50+ is older workers.

[7] A number of studies have examined related issues using firm level data. For example, see Aubert et al. (2006) and Schone (2009).

Finally, we decompose the skill-biased effect of technology on labour compensation into changes in the employment shares and relative wages. We find that relative wages are deskilling over a long period while skill-biased demand is mainly reflected in the skill-biased changes in employment shares, which is consistent with the findings of Mallick and Sousa (2017). We also test the speed of adjustment of wage shares to technological changes using a dynamic panel model incorporating an error correction mechanism and reject the assumption of inertia in wage shares adjustment.

The rest of this paper is structured as follows. Section 2 introduces the empirical model involving education, gender and age bias. Section 3 describes the data. The empirical results are presented and discussed in Section 4 and Section 5 contains some concluding remarks.

2. Empirical specification

The empirical specification used in this paper to analyse the impact of technology on the wage shares of skilled and unskilled workers is based on, among others, Chun (2003) and O'Mahony et al. (2008). Wage shares are assumed to depend on the capital-output ratio and the share of ICT capital in total capital. As a first step, total labour cost in industry *i* at time *t* is expressed as a function of the average wage of the different groups of workers, the stock of capital and real output as follows:

$$LC_{it} = f(pa_{jit},...., pa_{nit}, K_{it}, Y_{it}) \tag{1}$$

LC_{it} is the labour cost in industry *i* at time *t*; pa_{jit} is the wage rate for the *j*-th age group and *n* is the total number of age groups; *K* is total capital; and *Y* is real output.

Equation (1) is a general specification. In order to operationalise this relationship, we assume a translog cost function. Applying Shephard's lemma on the assumed translog functional form, labour cost share equations for each category of workers can be derived as:

$$\left(\frac{wa_{jit}}{WT_{it}}\right) = \beta_i + \sum_{j=1}^{n} \beta_{w_j} \ln\left(\frac{pa_{jit}}{pa_{1it}}\right) + \beta_K \ln\left(\frac{K_{it}}{Y_{it}}\right) + \varepsilon_{it} \tag{2}$$

wa_{jit} is the wage bill of age group j in industry i and time t; WT_{it} is the total wage bill of the same industry; pa_{jit} is the wage rate of the jth age group; pa_{1it} is the wage of the baseline age group; and ε_{it} is the usual error term.

The capital-output ratio captures the degree of capital-skill complementarity. The existing evidence suggests the presence of capital-skill complementarity $(\beta_k > 0)$ for skilled workers (see, among others, Machin and Van Reenen, 1998; Chun, 2003). Based on the existing literature, the impact of technological change on the wage premium can be examined by augmenting equation (2) with an indicator of technology. Following O'Mahony et al. (2008), we use the ratio of ICT capital over total capital $\left(ICT/K_i \right)$ as a technology indicator and re-write equation (2) as follows:

$$\left(\frac{wa_{jit}}{WT_{it}}\right) = \beta_i + \beta_K \ln\left(\frac{K_{it}}{Y_{it}}\right) + \beta_{IT} \ln\left(\frac{ICT_{it}}{K_{it}}\right) + \eta_t D_t + \varepsilon_{it} \qquad (3)$$

In equation (3), following the existing literature (e.g., see Chun, 2003 and O'Mahony et al., 2008) and to avoid the endogeneity problem, the relative wage term has been replaced by time dummies (D_t). Technology is age biased in favour of young worker groups if $\beta_{IT} > 0$ for the young groups and $\beta_{IT} < 0$ for the older groups.[8] As discussed earlier, the expected effect on the senior groups could be positive or negative. The empirical analysis presented in this paper allows one to identify the actual direction of the impact of technology on the demand for workers in different age groups (i.e., young, senior and older). This paper sheds new light on the skill and gender biases of technology on the demand for older workers.

Heywood and Siebert (2009) argue that, historically, older workers in most countries have not been allowed to work and receive pension income at the same time. Pension rules discourage on-going relationships with existing employers. This is problematic, because some older workers may be highly valuable to firms that have incurred significant costs in hiring and training of these workers. Taxation laws in European countries tend to reduce hiring

[8] Related studies that focus on the skill or gender bias of ICT have used a similar approach. ICT is skill-biased in favour of the high skilled group if $\beta_{IT} > 0$ for the high skilled group and $\beta_{IT} < 0$ for the intermediate and unskilled groups. Similarly, ICT is gender-biased in favour of females if $\beta_{IT} > 0$ for the female older groups and $\beta_{IT} < 0$ for the male older groups.

opportunities and earnings for older workers, especially when wage setting is rigid (Hurd, 1996; Blau and Shvydko, 2011). Often, older workers are forced to retire early with low pensions. Labour market institutions that tend to be unfriendly towards older workers could make older workers more vulnerable to skill-biased changes in demand.

In order to disentangle the effect of skill-biased demand arising from institutional factors, we augment equation (3) with labour market institution variables extracted from the Institutional Characteristics of Trade Unions, Wage Setting, State Intervention and Social Pacts database (ICTWSS, Visser 2015; Jansen 2014).[9] We include seven labour market institution variables to capture the effect of institutional setting and restrictions: (i) Coordination of wage-setting (*COORD*, which varies on a scale of 0 to 5 with 0 = fragmented wage bargaining and 5 = extensively regulated wage bargaining; Kenworthy, 2001); (ii) Mandatory extension of collective agreements to non-organized employers (*EXT*, which varies from 0 = no mandatory extension or functional equivalent to 3 = virtually automatic and general extension); (iii) National Minimum Wage (*NMW*, which varies from 0 = No statutory minimum wage to 2 = Statutory national minimum wage); (iv) Social pact on wage issues (*WAGE*, 0 = no, 1 = yes);[10] (v) Social pact on old age/retirement pensions (*PENSIONS*, 0 = no, 1 = yes); (vi) Union density rate (*UD*) and (vii) Summary measure of centralisation of wage bargaining (*CENT*, 0-1; Iversen, 1999). The choice of labour market institution variables is dictated by data availability for all nine countries.

The labour demand equation incorporating the labour market institution variables is as follows:[11]

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[9] In a recent study, Conti and Sulis (2016) make an important contribution to the literature that deals with the impact of labour market regulations. Specifically, using data from several European countries, Conti and Sulis focus on the role that labour market regulations play in shaping the relationship between technology adoption and economic growth.

[10] Social pacts are defined as "… publicly announced formal policy contracts between the government and social partners over income, labour market or welfare policies that identify explicit policy issues and targets, means to achieve them, and tasks and responsibilities of the signatories…" (Avdagic et al., 2011: p.11). This excludes (a) tacit understandings or agreements that are not publicly announced; (b) bilateral agreements between employer organizations and trade unions that do not involve government as a negotiating party, even if the implementation requires legislative action or government support; and (c) the so-called symbolic or declaratory pacts that do not commit the negotiating parties to specific tasks and responsibilities (Visser, 2015).

[11] While we are extremely grateful to an anonymous reviewer for highlighting the role of differential changes in the statutory and effective retirement ages, compulsory education legislation and the expansion of higher education on skill biased demand for older workers across countries, due to lack of appropriate data, we are unable to explicitly take these factors into account. We believe that the time dummies and labour market institution variables included in our empirical model should capture at least some of the effect of these factors. We have however highlighted this issue as an area for further research towards the end of the conclusion.

$$\left(\frac{wa_{jit}}{WT_{it}}\right) = \beta_i + \beta_K \ln\left(\frac{K_{it}}{Y_{it}}\right) + \beta_{IT} \ln\left(\frac{ICT_{it}}{K_{it}}\right) + \beta_L LMI_t + \eta_t D_t + \varepsilon_{it} \tag{4}$$

In this paper, we mainly focus on the skill-biased labour demand (as measured by labour compensation shares by gender, age and education) for older workers. Caselli and Coleman (2006) however, emphasize that the skill-biased nature of technology helps in explaining the dramatic change in the relative supply of skill, as well as the skill premium when skilled and unskilled labour are imperfect substitutes. In a recent study, using data from the US manufacturing sector, Mallick and Sousa (2017) show that improvements in technology have a positive effect on skilled-to-unskilled labour and wage ratios. Thus, it is highly pertinent to link our work with the SBTC literature that focuses on relative wages (Autor et al., 1998). In order to accomplish this task, the left-hand side of equation (4) can be re-written as follows:

$$\left(\frac{wa_{jit}}{WT_{it}}\right) = \left(\frac{pa_{jit}Ea_{jit}}{pT_{it}ET_{it}}\right) = \left(\frac{pa_{jit}}{pT_{it}}\right)\left(\frac{Ea_{jit}}{ET_{it}}\right) \tag{5}$$

where pa_{jit} and pT_{it}, respectively, are the average wage of the age group j in industry i and the average wage of all age groups in the same industry.

Equation (5) shows that labour compensation share $\left({wa_{jit}}/{WT_{it}} \right)$ of the age group j in industry i can be decomposed into relative wage $\left({pa_{jit}}/{pT_{it}} \right)$ and employment share $\left({Ea_{jit}}/{ET_{it}} \right)$ of the age group j in industry i .In equation (3), changes in the relative wage or employment shares are captured by the time dummies; similarly, we now specify the relative wage and employment share equations as follows:

$$\left(\frac{pa_{jit}}{pT_{it}}\right) = \beta_i + \beta_K \ln\left(\frac{K_{it}}{Y_{it}}\right) + \beta_{IT} \ln\left(\frac{ICT_{it}}{K_{it}}\right) + \beta_L LMI_t + \eta_t D_t + \varepsilon_{it} \tag{6}$$

$$\left(\frac{Ea_{jit}}{ET_{it}}\right) = \beta_i + \beta_K \ln\left(\frac{K_{it}}{Y_{it}}\right) + \beta_{IT} \ln\left(\frac{ICT_{it}}{K_{it}}\right) + \beta_L LMI_t + \eta_t D_t + \varepsilon_{it} \tag{7}$$

Equations (6) and (7) can be used to separately examine the impact of ICT on relative wage and employment shares.

3. Data description

A comprehensive analysis of labour demand by country and industry is now possible following the construction of the EU-KLEMS labour and capital accounts database. (See O'Mahony and Timmer, 2009 for details. The analysis presented in this section is based on data collected from nine EU countries (Austria, Belgium, Denmark, Spain, Finland, Germany, Italy, the Netherlands and the UK). These countries are selected mainly because of the availability of data on the relevant variables. Specifically, data on labour composition cross-classified by gender, age and education are available in EU-KLEMS. Based on Afonso's (2016) country categorization with a focus on labour market institutions, our sample includes four Continental Europe countries (Austria, Belgium, Germany and the Netherlands), two Nordic countries (Denmark and Finland), two Mediterranean countries (Italy and Spain) and one Anglo-Saxon country (the UK).

The panel data used in this paper are based on 11 industries that together make up the market economy and employs the EU-KLEMS industry division into agriculture, forestry and fishing (AtB); ICT producing industries including computing equipment, electrical and electronic equipment, instruments and telecommunications equipment and services (ELECOM); a three way split of the remainder of manufacturing into consumer goods (Mcons), intermediate goods (Minter) and investment goods (Minves); a group combining mining, utilities and construction (Other G); wholesale and retail trade (50t52); transport (60t63); financial services (J); business services (71t74) and personal services including hotels and catering (PERS).

Output is approximated by real value added and the capital measure is divided into ICT and non-ICT components, using Törnqvist capital services indices comprising three assets categories within ICT capital (computer, software and communications equipment) and three within non-ICT capital (structures, non-ICT equipment and vehicles). Capital stocks are estimated for each asset using the perpetual inventory method, assuming exponential depreciation with rates that vary across industries but are assumed to be identical in the same industry in the nine countries (Timmer et al., 2007a). Indices of capital services were then derived by weighting the growth rate of each asset type by its share in the nominal value of total capital services employing user costs rather than asset acquisition prices. The investment data for computers already incorporates a hedonic adjustment.[12]

[12] The EUKLEMS uses one set of asset depreciation rates that vary across asset type and industry but not across countries and over time (Fraumeni, 1997). There are 9 asset types in the capital account of which three assets are ICT assets: Computing equipment, Communications equipment and Software. Depreciation rates for non-ICT

In addition, wage and employment data broken down by gender, education and age levels were derived from national micro data sources, such as Labour Force Surveys (see O'Mahony and Timmer, 2009, for details). A direct comparison of skill levels is difficult in an international context since training and educational systems vary cross countries. We divide employees into three groups: high (with college degrees and above), intermediate (with education or training qualifications below a college degree) and unskilled (no qualification). The age dimension is also categorized into three groups: young (15-29), senior (30-49) and older (50 and above). Table 1a presents descriptive statistics of the labour compensation variables of older workers from 1970-2007. Due to unavailability of data for older workers, the time periods for wage shares differ across countries (1970-2007 for Finland, Italy and the UK; 1979-2007 for the Netherlands; 1980-2007 for Austria, Belgium, Denmark and Spain; and 1991-2007 for Germany). These results are weighted by average employee compensation (COMP) share of each industry over the period 1970-2007, which is a standard approach to take account of industry heterogeneity (O'Mahony and Peng, 2009).

(Insert Table 1a-b around here)

Older males have the highest wage shares in Spain (20.5%), followed by Germany (18.2%), the Netherlands (17.8%) and Denmark (17.4%). In other countries, older males account for around 15% of total wage bills except that the wage share of older males in Italy is only 5.4%. Compared with males, wage shares of older females are much lower (1% to 6.6%), which may be related to lower statutory pensionable ages (SPA) for females (Carmichael and Ercolani, 2014). Italy still has the smallest wage share (1%) for older females, suggesting low labour participation of older workers (Peng and Siebert, 2008).

Similarly, employment shares (measured by work hours (Timmer et al., 2007a) of older males are also higher in Spain, Germany, the Netherlands and Denmark, and lower in Italy. Relative wages of older males exceed 1, suggesting higher wages than the average wage within the same industry. The only exception to this is Italy, where older male wages are about 30% below the average wage. In Austria and the UK, respectively, the relative wage of older

assets by industry are shown in Appendix Table 1 in Timmer et al. 2007a. The rates for other machinery, transportation equipment and non-residential buildings differ by industry. The depreciation rate for residential structures is set to 0.014. The three ICT assets are assumed to have the same depreciation rate for all industries. These were set equal to the rates employed in Jorgenson et al. (2006), i.e. 0.315 for computers and software and 0.115 for communications equipment. The rate for other immaterial assets was set equal to software, infrastructure to non-residential buildings, and products of agriculture and other products to other machinery and equipment (van Ark et al. 2008).

females is 1.1 and 1.0. The relative wage of older females in Italy is the lowest (0.6) and the same applies to the employment share (2.3%). It will therefore be interesting to analyse the variation in labour compensation shares across countries by decomposing this variation into employment share and relative wage variations. Lower employment shares combined with lower relative wages, as evident in Italy, might reflect worsening labour demand for older workers.

Table 1b presents descriptive statistics of capital-output and ICT capital-total capital ratios over the period 1970-2007 (1976-2007 for Austria). The average capital-output ratio is the highest in Austria (58.8%), followed by Belgium (53.7%) and Italy (51%). Spain (32.9%), the UK (34.8%), the Netherlands (39.2%) and Germany (39.4%) have the lowest capital-output ratios. At the country level, we find a broad negative correlation between capital-output ratio and wage shares of older workers. Specifically, countries with higher capital-output ratios are more likely to employ fewer older workers or pay lower wages and *vice versa.* For example, Spain has the lowest capital-output ratio among these countries as well as the highest wage share of older males. On the other hand, Italy has the lowest wage share for both males and females but it is among the top three countries for capital-output ratio. Thus, at the country level, there is evidence of a substitution (or skill-biased) effect involving older workers - labour is being substituted for capital.

Skill-biasedness of technology is examined by means of the average ICT capital to total capital ratio, which is highest in the UK (10.3%) and lowest in Italy (4.4%). A positive correlation between skill-biased technology and the wage shares of older males is found for these countries. This positive correlation also broadly fits the situation of older females. For example, Italy has the slowest adoption speed for ICT as well as the lowest level of wage shares. Spain, with a relatively high ICT ratio has the highest wage share of older males. Thus, there is a complementary or deskilling effect of ICT capital on the demand for older workers at the country level.[13]

Table 1b also presents descriptive statistics of the labour market institution variables. Highly coordinated wage setting exists in all Continental and Nordic countries (COORD ≥

[13] The definition of ICT assets has not been completely harmonized across the EU. In some countries, IT is defined broadly as office and computing equipment, whereas others used a more narrowly defined category of computers only. Similarly, CT investment in some countries is defined as investment in all products with electrical components and radio/television transmitters/receivers, while others also include insulated wire and cable, instruments and appliances for measuring, checking, testing, navigating and other purposes. While harmonization is highly desirable, it may be hard to achieve it unless detailed information on all types of investments is made available by all countries but serious differences in definitions remain (Timmer et al. 2007 a and b).

3.68), but it is relatively weak in the Mediterranean and Anglo-Saxon countries (COORD ≤ 3.1). There seems to be little or no legal provision for mandatory extension of collective agreements to non-organised employers in the Mediterranean and Anglo-Saxon countries (EXT ≤ 0.29) but extension is virtually automatic in Continental and Nordic countries (EXT ≥ 1), with two exceptions of Denmark (EXT = 0) and Spain (EXT = 3). Belgium, the Netherlands, Spain and the UK have a national minimum wage (NMW > 0). Regarding social pacts in Europe, Table 1b shows that the social pact in Finland is highly likely to be about wage issues (WAGE = 0.34). A social pact on old age/retirement pensions is likely only in Belgium (PENSIONS = 0.13) and the Netherlands (PENSIONS=0.08). Compared to other countries included in our sample, the two Nordic countries of Denmark (73.14%) and Finland (70.71%) have much higher union density (UD). Wage bargaining is relatively more centralised in all Continental and Nordic countries (CENT ≥ 0.44) but it is relatively weak in the Mediterranean and Anglo-Saxon countries (CENT ≤ 0. 33). With a long history of evolution, labour market institutions exhibit a complex pattern in European countries but, in general, we can say that the labour markets of Continental and Nordic countries are more regulated than those of the Mediterranean and Anglo-Saxon countries.

(Insert Figure 1 about here)

It is however worth pointing out that cross-country comparison of the averages tends to ignore the dynamics of the long-term unbalanced panel data for each country and may lead to misleading conclusions. Figure 1 shows the evolution of wage shares (in %) for workers aged 50 and above in each country. We find a down-and-up trend in most countries. This pattern suggests worsening labour market conditions for older male workers during the 1970s and 1980s as Europe started to experience the population aging phenomenon (Carmichael and Ercolani, 2014). However, there is evidence of some recovery during the 1990s, which continues into the 2000s, surpassing the 1980s level. Especially after 1990, there is a fast acceleration in wage shares of older workers in all Continental, Nordic and Anglo-Saxon countries. This evidence suggests the presence of a structural break around 1990 in the wage shares of older males in these countries. In contrast to the acceleration in other countries after 1990, the declining periods in the two Mediterranean countries (Italy and Spain) lasted till the 2000s. There is evidence of a long-term worsening of the wage shares of older workers in Italy and Spain.

(Insert Figure 2 about here)

In the same vein, the simple averages presented in Table 1b cannot adequately capture the significant increase in investment in new technology after 2000 (see Figure 2). In the last year of our sample, the ICT capital ratios have been up to 30% in Denmark and the UK, 25% in Belgium, Finland and Netherlands, which is consistent with fast adoption of new ICT technology. Austria, Spain and Germany experienced a slower but steady adoption of new technology (up to 20%) over the last forty years. As expected, Italy had the lowest growth in ICT capital ratios (less than 10%). The UK, the Netherlands and Scandinavian countries are the leaders when it comes to absorption of new technology, while the continental European countries joined the ICT revolution at a later stage (Basu et al., 2003; Van ark et al., 2008).

4. Empirical Results

4.1 Aggregated data for all nine EU countries

Wage share equations specified in equation (3) were estimated for all age groups in each country using a fixed effect estimator (FE) that controls for industry, year and country fixed effects. Following the existing studies (e.g., Kahn and Lim, 1998 and Chun, 2003), these regressions were weighted by average employee compensation (COMP) share of each industry over the period 1970-2007. This allows one to take account of industry heterogeneity. We also control clustering of observations at the country and industry level that affects standard errors. Results from fixed effect regressions across the entire sample are presented in Table 2.

For young workers (15-29 years old), capital appears to be a substitute for males even when they have higher educational attainment; the estimated coefficients of the high and intermediate-skilled workers, respectively, are -0.349 and -1.28. However, the impact of the capital-output ratio on the wage share of female workers is statistically insignificant, possibly due to earnings rigidity of young females in Europe. The estimated coefficient of the technology term suggests that ICT increases the wage shares of the highly skilled young male workers (0.155) at the expense of unskilled workers (-1.767). The estimated effect of ICT on the wage share of highly skilled young females is positive and significant; the estimated coefficient is 0.106, but the impact on intermediate-skilled young females is negative and significant (-0.909). The wage share of unskilled young female workers appears to be unaffected by ICT.

(Insert Table 2 about here)

In the case of senior workers (30-49 years old), the estimated results concerning the impact of the capital-output ratio on the wage shares are mixed. For the high-skilled group, capital appears to be complementary for females with an estimated coefficient of 0.549 but is insignificant for males. The reverse is true for the unskilled group with a significant positive on the male wage share (1.734) but an insignificant effect on the female wage share. The estimated results presented in Table 2 suggest that ICT increases the wage share of both high and intermediate-skilled males (0.545 and 2.722) at the expense of unskilled males (-1.054). ICT also increases the wage share of high-skilled senior female workers (0.313), but its impact on the wage share of intermediate and unskilled senior female workers is statistically insignificant.

We now turn our attention to older workers (50 and older). The results presented in the bottom panel of Table 2 suggest that the impact of the capital-output ratio on the wage share of older high-skilled female workers is positive and statistically significant; the estimated coefficient is 0.139. ICT capital increases the wage shares of highly skilled males (0.274) at the expense of unskilled males (-0.459). However, in the case of older female workers, ICT increases the wage shares of both high and intermediate-skill workers (0.069 and 0.186).

The FE estimation results presented in Table 2 support the idea that ICT and high skill are complementary. For all nine countries, ICT has a negative impact on the wage shares of unskilled workers. However, in the case of high and intermediate skill groups, this impact tends to be positive. We generally observe a positive relationship between technology and skill, although the skill-biased demand is much stronger in the case of senior workers than for young and older workers, which is consistent with the results in Autor et al. (1998).

4.2 GMM estimation

The FE estimation results presented so far assume exogenous technology. Due to difficulty in finding an appropriate instrument for technology, a large number of existing studies have relied on this assumption (e.g., see Berman et al., 1994; Autor et al., 1998; and Chun 2003). In this section, we present the results of Generalised Method of Moments (GMM) estimation, where lagged values of the explanatory variables are used as instruments (Baum et al., 2003).[14]

[14] The use of lagged values is not ideal but it represents an improvement over FE estimation.

GMM estimation involves the use of instrumental variables (IV), which must satisfy two requirements: the instrument must be correlated with the included endogenous variables but orthogonal to the error term. Given that we are using lagged values of the explanatory variables, the first requirement is likely to be met. The orthogonality requirement is checked with an over identification test (Hansen *j* statistic) in the presence of heteroskedasticity. This is a test for the joint hypotheses of correct model specification and the orthogonality conditions. The null hypothesis is that all instruments are valid. A rejection of the null hypothesis implies that the instruments are not satisfying the required orthogonality conditions. After GMM estimation, we also calculate what Hayashi (2000) calls the *C* statistic (also known as the difference-in-Sargan statistic). This test is used to determine the exogeneity of the endogenous regressors, which allows one to establish the usefulness of the GMM method.[15] As with the case of FE estimation, we correct the heteroskedasticity-robust standard errors for the clustering of observations at the country*industry level in the GMM estimation. The Hansen *J* statistic and the *C* statistic are also robust to clustering.

(Insert Table 3 about here)

Results for the GMM estimation are presented in Table 3. These results are not significantly different from the ones presented in Table 2. In general, the GMM estimation also supports the skill-biased technical change hypothesis in that ICT favours high skilled, female or senior workers. In all estimated equations, the Hansen *J* statistic is insignificant. Hence, we cannot reject the null hypothesis of orthogonality between the instrumental variables and the error term. However, while the GMM estimation leads to some gain in consistency, compared to FE estimation, it also reduces the efficiency of the estimates. The gain in consistency must be balanced against the loss in efficiency. At the 10% significance level, there is insufficient evidence to reject the null hypothesis associated with the *C* statistic, suggesting that the use of GMM will lead to loss in efficiency. Therefore, in the remainder of this paper, we present only FE estimation results.

4.3 ICT and wage shares of older workers in each of the nine countries

[15] The null hypothesis of the *C*-test is that the FE estimator is efficient and consistent. Failure to reject the null hypothesis implies that FE estimates are preferred over the GMM estimates.

The results presented so far are based on data pooled across countries and industries. Although dummy variables were included to account for both fixed effects, it is possible that the impact of this diversity was not fully captured. Accordingly, we also separately estimated the wage share equation for each country. The empirical results concerning the impact of ICT capital on the wage shares of older workers are reported in Table 4.[16] These results (i.e., the estimated coefficients of the ICT-Total Capital ratio) suggest that, in a number of EU countries, the technology is significantly biased against high-skilled older workers in the sense that an increase in ICT capital decreases the wage share of these workers. For example, the estimated coefficients for Belgium and Germany for older males, respectively, are -1.523 and -0.87, whereas for Danish females the estimated coefficient is -0.182. The age dimension reflects the skilled-biased demand not measured by the education dimension. In the case of Belgium, Germany and Denmark, technology appears to have a negative impact on the wage shares of older workers even though these workers are highly educated.

Skill-biased demand against older workers is also found in the intermediate-skilled groups: Germany (-1.906) for males, Belgium (-0.807), Denmark (-0.669) and Germany (-0.477) for females. ICT has a negative impact on the wage share of unskilled female workers in the Netherlands (-0.166). These results are consistent with existing studies (e.g., see Caroli and Van Reenen, 2001; and Goux and Maurin, 2000). It has been argued that the combined effect of wage rigidity and a high unemployment rate, as well as the increasing number of low-skilled jobs held by highly educated over-qualified workers can lead to this outcome (Pierrard and Sneessen, 2003 and Barros et al. 2011). There is also some evidence that employment protection legislation (EPL) has an adverse effect on firms that innovate. Labour market institutions make it very hard for such firms to adjust their skill composition (Pierre and Scarpetta, 2006). It is therefore difficult to observe technology driven responses to demand for skills.

(Insert Table 4 about here)

Table 4 shows that the impact of ICT on wage shares of highly skilled older workers is insignificant or significantly negative. However, in the case of the pooled data, as reported in Table 2, we found a significant positive relationship between the two variables. It seems that the positive effect reported in Table 2 was mainly due to cross-country variations, which could

[16] Full results are available to interested readers upon request.

be attributed to labour market rigidities such as EPL. It is generally believed that strict EPL inhibits labour market flexibility by reducing the ability of the firms to adjust the workforce during changing economic conditions (Zhou, 2006). In contrast to the high-skilled older workers, ICT has a positive impact on wage shares of unskilled older workers in Austria (males, 0.647) and Germany (males, 1.055 and females, 0.845). Therefore, as noticed in the descriptive statistics presented in Table 1 a-b, there is a complementary or deskilling effect of ICT capital on the demand for older workers.

4.4 The impact of technology on older workers over time

In Table 4, we find evidence of significant deskilling among older workers in Austria, Belgium, Denmark and Germany. Our empirical analysis suggests that highly skilled older workers have been replaced by unskilled older workers. Historically, changes in technology have been associated with deskilling of the labour force over time.[17] The substitution of machines for skilled labour during the industrial revolution and the move towards Fordist manufacturing techniques in the 1950s are the most widely cited examples (e.g., see Goldin and Katz, 1998; and O'Mahony et al., 2008). Are similar processes at work in the case of ICT? It could be argued that much of the observed skill bias may be a short-term adoption effect. As the new technology becomes fully integrated into the production process, firms can replace the high-wage, highly educated young and senior workers with low-paid, less-educated older workers. Within the older worker groups, it is also possible to substitute high-skilled workers with their unskilled counterparts.

The aim of this section is to focus on possible changes in the impact of technology over time. Using a structural break test, we split the full sample into two sub-samples in terms of the time periods. Using the sub-samples, we analyse the differences in the relevant estimated coefficients over time. If technology is deskilling, we would observe a shift in labour demand from highly skilled to lower skilled (i.e., intermediate and low-skilled) workers. This shift in demand for workers is likely to result in a shift in the impact of technology in our wage shares equation estimates.

In order to examine whether or not the impact of ICT on older workers in each of the nine EU countries is de-skilling, we focus on changes in the estimated coefficient of ICT in our wage share equation over time. We use a two-step approach: first, we test for structural breaks in the country-level data and second, we re-estimate equation (3) taking the structural breaks

[17] An interesting discussion of how and why deskilling occurs can be found in Piore (1979).

into account. The econometric literature on structural break tests for panel data is still evolving and no formalised tests are readily available. We follow Stiroh (2002) and O'Mahony et al. (2008) in testing the aggregated data for a break and then use the results to re-estimate the wage share equation for the subsamples. We then analyse the changes in the relevant estimated coefficients over time. In order to identify the break date, we use the Quandt Likelihood Ratio (QLR) test (also known as the "sup-Wald" statistic), which is a modified version of the Chow test for structural change. The breakpoint is defined as the maximum value of the statistic with the null hypothesis of no structural change in the middle range of the data (15%-85% range with 15% trimming).

(Insert Table 5 about here)

Results of the estimated breakpoints for each country are reported in Table 5. We find that the breakpoints differ across countries and skill groups, which is in line with a priori expectations, given the heterogeneity in the cross-country data. This heterogeneity can be largely attributed to differing economic and institutional factors. The null hypothesis of no structural break can be rejected for all gender/education groups of older workers in all nine countries. Except for Germany, the Netherlands and the UK with only one maximum value, two local maximum values of the QLR statistic were found in the case of all other countries, suggesting two breakpoints. This could be attributed to, among other things, rigidity of the wage setting arrangements, the impact of new technology and differences in the speed of technology adoption. In this paper, we also address the trade-off between the alleged decrease in learning capabilities (damaging older workers) and the increase in experience and seniority (in favour of older workers). The structural breaks in deskilling arise not only from the codification and standardization of new technology but also from the change in labour supply. Exposure to the ICT on the part of the young and senior workers in the 1970s and 1980s could have helped them become more adaptable to new technology in their later career as they became older workers in the 1990s and 2000s (Messinis and Ahmed, 2013; Barros et al., 2011).[18]

Using the estimates of the break points, we re-estimate equation (3) after interacting each variable with appropriate time dummies to capture the structural break. For each country, we use the average of the break-dates of all gender/education groups of older workers. It

[18] We are grateful to a referee for bringing this issue to our attention.

appears that Finland experienced structural breaks from the impact of new technology much earlier (around 1984 and 1994) than other countries (around 1990 or 2000). In the case of Germany, we found one structural break around 2003.[19] The findings of this re-estimation are presented in Table 6, where we continue to focus on the estimated coefficients of ICT/K for older workers group over different time periods.

(Insert Table 6 about here)

The empirical results presented in Table 6 show an increasing skill-biased impact of technology on the wage share of the highly skilled older male workers in Denmark (0.266 and 0.719) and Germany (0.381), as well as female workers in Belgium (0.114 and 0.346), Denmark (0.257), Finland (0.364 and 1.958), Germany (0.144) and the UK (0.313). The skill-biased labour demand for new technology is also reflected in the negative impact on wage shares of unskilled old female workers in Austria (-0.557), the Netherlands (-0.164) and the UK (-0.597), and for male workers in Germany (-0.327). The impact of technological change on wage shares increases particularly in the later years of our sample (i.e., during the 2000s).

The deskilling effect of new technology is evident in the results presented in Table 6; the demand for highly skilled (unskilled) older workers is decreasing (increasing). The effect of new technology becomes significantly negative for high skilled older males (the relevant estimated coefficient for Belgium is -1.53; Finland -0.31 and Germany -0.889) and females (with an estimated coefficient for Denmark is -0.096). At the same time, it is interesting to note that the wage share of unskilled older workers has increased with ICT in many countries: for males, the estimated value of the relevant coefficient is 0.876 for Austria; 0.703 for Belgium; 0.614 for Finland; 1.076 for Germany; 0.141, 0.337 and 0.612 for Italy. In the case of the females, the estimated value of the relevant coefficient is 0.745 for Spain; 0.849 for Germany. Therefore, we can conclude that the skill-biased demand is evident for the older workers in Denmark, the Netherlands and the UK, while in Spain and Italy, the evidence of deskilling is widely observed. For other European countries (such as Austria, Belgium, Finland and Germany), skill-biased or deskilling labour demand from new technology varies by gender and over different time periods, suggesting heterogeneous patterns of adaptation to new technologies.

[19] The required data on all variables for Germany is not available before 1991 due to reunification.

4.5 Skill biased demand and labour market institutions

In this section, we extend the empirical model to include labour market institution variables. Specifically, we attempt to examine the impact of labour market institutions on skill-biased demand for older workers, which involves estimation of equation (4). The estimated results are reported in Table 7.

Compared to the estimates without labour market institution variables presented at the bottom panel of Table 2, we find that our basic conclusion concerning the skill-biased demand for older workers continues to hold. The impact of the capital-output ratio on the wage share of older workers is still positive and statistically significant only in the case of high-skilled females with an estimated coefficient of 0.132. ICT capital decreases the wage shares of unskilled males (-0.557) but the estimated coefficient on ICT capital on high-skilled males is now statistically insignificant. In the case of older female workers, ICT capital increases the wage shares of both high-skilled (0.064) and unskilled workers (0.253) but the impact on the intermediate-skilled workers is statistically insignificant. Thus, once we take labour market institutions into account, ICT continues to favours high-skilled female workers, but the deskilling effect on unskilled females is more significant.

(Insert Table 7 about here)

The labour market institution variables show a complicated pattern in cross-country regressions. For example, coordination of wage setting (COORD) decreases the wage shares of highly skilled males (-0.084) but its effect is statistically insignificant for all other groups. Extension of collective agreements (EXT), social pact on pensions (PENSIONS) and centralisation of wage bargaining (CENT) appear to have a negative impact on wage shares of highly skilled older workers, or a positive effect on wage shares of unskilled workers. It can be argued that strong labour market institutions can alleviate the adverse effect of the skill biased demand on wage shares of older unskilled workers.[20] The impact of a national minimum wage (NMW), social pact on wage issues (WAGE) and union density (UD) on wage shares of high and intermediate-skilled older workers is positive, which supports the skill-biased demand for older skilled workers.

4.6 Sensitivity test using relative wages and employment share as dependent variables

[20] This result is consistent with Acemoglu et al. (2001), Peng and Kang (2013) and Kristal and Cohen (2016) who have reported that labour market regulation can depress wage inequality.

So far, we have used the labour compensation shares as the dependent variable. In order to link our work with SBTC literature (see towards the end of Section 2), we decomposed the labour compensation shares into employment and relative wages. To test the SBTC hypothesis, the skill-biased effect on relative wages has to be disentangled from the changes in employment shares (Autor et al., 1998; Mallick and Sousa, 2017). Table 8 presents the estimated results when relative wages of older workers are used as the dependent variable as specified in equation (6). The impact of the capital-output ratio on relative wages of older workers is positive and significant only in the case of unskilled males with an estimated coefficient of 0.335. ICT capital increases the relative wages of unskilled males (0.091) and females (0.073), but the impact on high and intermediate-skilled workers is statistically insignificant. Based on the results presented in Table 8, it seems that the SBTC hypothesis is invalid in the case of the countries in our sample.

(Insert Table 8 about here)

Compared to the estimates of labour compensation shares, the relative wages of older workers exhibit a deskilling trend. Specifically, the impact of ICT capital ratios on relative wages of unskilled workers is positive and statistically significant. It follows that, the skill-biased demand for older workers arises due to decreasing employment shares of unskilled older workers and increasing employment shares of high-skilled older workers. In order to formally test this hypothesis, equation (7) is estimated, where the employment shares are the dependent variables. The estimated results, as shown in Table 9, are qualitatively similar to those presented in Table 7, where the labour compensation shares are the dependent variables. The estimated coefficient of the ICT capital is larger in magnitude (-0.69 for unskilled males; 0.091 for high skilled females). Our results are consistent with Mitchell (2005), who argues that even with an increasing demand for skilled labour over time, specialization is deskilling. Mallick and Sousa (2017) show that technology has become more favourable to skilled workers in the US since the 1980s and this has resulted in relative abundance of skilled workers.

(Insert Table 9 about here)

The results presented in Tables 8 and 9 show that new technology increases the employment shares as well as relative wages of only unskilled older female workers. The deskilling demand for unskilled older females suggests that unskilled female-dominant services such as the hospitality, nursing assistants, primary teaching assistants and community care are complementary to new technology. ICT might be adopted in more codified and standardised forms to allow unskilled older females to operate in the above-mentioned service sectors. These results further corroborate the idea that new technologies are not equally beneficial to all industries. In other words, as shown by Mallick and Sousa (2017), the impact of technology is subject to some degree of heterogeneity.

4.7 Dynamic specification

If the wage shares are persistent and path dependent then their adjustment to the shocks arising from capital, new technology and labour market institutions may be very slow. In such a case, the static empirical model presented in equation (4) is likely to lead to biased and inconsistent results (Baltagi and Blien, 1998; Buttner, 1999). Accordingly, in this section, we re-estimate our model using a dynamic panel specification that incorporates an error correction mechanism (Hamilton, 1994; Ammermuller et al., 2010):

$$\Delta\left(\frac{wa_{jit}}{WT_{it}}\right) = \beta_i + \beta_W\left(\frac{wa_{jit\text{-}1}}{WT_{it\text{-}1}}\right) + \beta_K \ln\left(\frac{K_{it}}{Y_{it}}\right) + \beta_{IT}\ln\left(\frac{ICT_{it}}{K_{it}}\right) + \beta_L LMI_t + \eta_t D_t + \varepsilon_{it} \qquad (8)$$

where the dependent variable (labour compensation share) is in the form of first differences; the lagged dependent variable is also among the right-hand side regressors to capture the possible inertia of wage shares adjustment.

Once the dynamic model has been estimated, using some simple parameter restrictions, we can test certain hypotheses. For example, when $\beta_w \approx 0$ or insignificant, the impact of new technology and institutions can be absorbed by the contemporaneous changes in the wage shares and hence the wage shares could not be persistent and path dependent. When $\beta_w \approx -1$, equation (8) reduces to a standard specification of the wage share (see equation (4)). When $0 < |\beta_w| < 1$, we get a more standard partial adjustment wage share equation.

The results of dynamic panel estimation are presented in Table 10. The coefficients of the lagged wage shares are significant but close to zero, which suggests that wages shares adjust quickly to shocks from capital, new technology and institutions. We still find the skill-biased demand for high-skilled older females with an estimated coefficient of 0.005. As the wage shares of older workers are not significantly persistent and path dependent, we cannot reject the static wage share equation in favour of a dynamic specification. In overall terms, our basic results from estimation of equation (4) are robust.

(Insert Table 10 around here)

5. Concluding Remarks

Over the past three decades, population aging has emerged as an important issue, especially in the developed countries. At the same time, the world economy has also greatly benefitted from technological advances. This paper aims to contribute to the literature that deals with the interaction between aging workers and technology. Using a unique industry level dataset, we attempt to examine the extent to which skill-biased technological change is evident at different points in the age distribution of workers in Europe. The main issue addressed in this paper is whether ICT is ultimately deskilling in the longer run and, if it is, does this affect older workers more? We also address the issue of whether the skill requirements are different in the post-adoption phase of the new technology. We believe that this issue is important as Europe, in particular, faces the problem of an aging workforce and yet the use of legislation to allow workers to continue past a culturally established retirement age needs to be balanced against the likelihood of the obsolescence of worker skills as technology changes.

We focus on nine European countries, where the number of older workers (aged 50 and over) has significantly increased over time. At the same time, the wage share of older workers in these countries has also widely fluctuated. We examine the impact of information and communication technology (ICT) on the wage shares of high-skilled, intermediate-skilled and unskilled male and female workers. The impact of ICT on the wage share of highly skilled male and female workers across all three age groups is positive and significant.

We also consider the impact of ICT on the wage shares of three age groups of male and female workers in each of the nine countries. We find significant differences across countries and over time. There is a complementary or deskilling effect of ICT capital on the demand for older workers. We also used the Quandt Likelihood Ratio (QLR) test to identify structural breaks for all countries over time. We find that skill-biased demand is evident for older workers in Denmark, the Netherlands and the UK, while in other European countries, especially in Spain and Italy, the evidence of deskilling is widely observed. Thus, either these groups of older workers are gradually becoming familiar with the new technology and/or they are involved in low skill non-routine tasks that cannot be easily substituted by computers (Autor et al., 2003).

Finally, we considered the impact of labour market institutions on wage shares of older workers and found that a national minimum wage, a social pact on wage issues and union density mostly benefit skilled workers, while coordination of wage setting, extension of collective agreements, a social pact on pensions and centralisation of wage bargaining can alleviate the adverse effects of skill-biased demand on the wage shares of older unskilled workers. From a policy point of view, our findings highlight the important role that governments can play by boosting public sector investment in education and job training programs with a focus on information and communication technologies, not only for young workers but also for older workers (Barros et al. 2011). Codified and standardized technologies can help older workers adapt to fast-changing working conditions and keep their jobs, while the trained young workers will be more adaptable to new technologies when they become senior and older workers, as can be seen from the structural breaks in the wage shares of older worker in our sample in the 1990s and 2000s. The empirical analysis presented in this paper suggests that labour market institutions have a positive impact on the earnings of the older workers. However, while examining the impact of these institutions on workers, one must keep in mind differing worker skills and industry heterogeneity.

Future research in this area should be based on improved measures of worker skill endowments. Messinis and Ahmed (2013) highlight the significance of cognitive skills as a driver of innovation and diffusion, and recommend a new measure of human capital (a composite index) that takes into account education, cognitive skill, life expectancy and the use of ICT. The proposed composite index could also take into account international test scores that allow a comparison of the education quality across countries. Different countries upgrade their educational systems at different times, which makes it harder not only to measure but also to compare the skill endowments of older workers across countries. In general, one has not only to try to reduce the potential but also the extent of the endogeneity problem (Heckman et al. 2006). Improved measures that also consider time-varying returns on education, skill obsolescence, skill-job mismatch and over-education are highly desirable (Barros et al. 2011).

Finally, it is worth mentioning that, in this paper, we only provide a suggestive interpretation of our estimated results as industry level data do not contain information on individual tasks. Further analysis based on micro data could shed more light on these issues. The age structure of the population varies across countries and this variation can also affect the economic performance of a country. Similarly, different countries upgraded their educational systems at different times but we have not taken this into account. The quality of the research on skilled biased demand for older workers can also be further improved by taking into account the changes in compulsory education legislation and the expansion of higher education across countries (e.g., see Marouani and Nilsson, 2016).

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References

Acemoglu, D. (1998). Why do new technologies complement skills? Directed technical change and wage inequality. Quarterly Journal of Economics 113, 1055-1089.

Acemoglu, D. (2003). Cross-country inequality trends. The Economic Journal 113, F121-F149.

Acemoglu, D. (2015). Localised and biased technologies: Atkinson and Stiglitz's new view, induced innovations, and directed technological change. Economic Journal, 583, 443-463.

Acemoglu, D., Aghion, P., and Violante, G.L. (2001). Deunionization, Technical Change, and Inequality. Carnegie-Rochester Conference Series on Public Policy 55, 1: 229-264.

Acemoglu, D., Autor, D.H. (2011). Skills, tasks and technologies: implications for employment earnings. In O. Ashenfelter and D. Card (eds.), The Handbook of Labour Economics. Amsterdam: Elsevier, 1043-1171.

Adermon, A., Gustavsson, M. (2015). Job polarization and task-biased technological change: Evidence from Sweden, 1975-2005. The Scandinavian Journal of Economics, 117, 878-917.

Afonso, Ó. (2016). Effects of labour-market institutions on employment, wages, R&D intensity and growth in 27 OECD countries: from theory to practice. Economic Modelling, 53, 48-62.

Ammermuller A., Lucifora C., Origo F. and Zwick T. (2010). Wage flexibility in regional labour markets: Evidence from Italy and Germany, Regional Studies 44, 401-21

Avdagic, S., Rhodes, M., and Visser, J. (2011), editors. Social Pacts in Europe. Oxford University Press.

Anger, S. (2011). The cyclicality of effective wages within employer–employee matches in a rigid labor market. Labour Economics 18(6), 786-797.

Aubert, P., E. Caroli and Roger, M. (2006). New technologies, organization and age: firm-level evidence. The Economic Journal 116(509), F73-F93.

Autor, D.H., (2015). Why are there still so many jobs? The history and future of workplace automation. Journal of Economic Perspectives, 29, 3-30.

Autor, D. and Dorn, D. (2009). This job is 'getting old': Measuring changes in job opportunities using occupational age structure. American Economic Review: Papers and Proceedings, 99, 45-51.

Autor, D.H., Dorn, D. (2013). The growth of low-skill service jobs and the polarization of the US labour market, American Economic Review, 103, 1553-1597.

Autor, D., Katz, L and Krueger, A. (1998). Computing Inequality: Have Computers Changed the Labor Market? Quarterly Journal of Economics CXIII, 1169-1214.

Autor, D., Levy, F. and Murnane, R, J. (2003). The skill content of recent technological change: an empirical exploration. Quarterly Journal of Economics 118(4), 1179-333.

Baltagi B. H. And Blien U. (1998). The German wage curve: evidence from the IAB employment sample, Economics Letters 61, 135-42.

Barros, C. P., Guironnet, J. P., and Peypoch, N. (2011). "Productivity growth and biased technical change in French higher education." Economic Modelling, 28(1-2), 641-646.

Basu, S., Fernald, J.G., Oulton, N., Srinivasan, S. (2003). The case of the missing productivity growth: or does information technology explain why productivity accelerated in the US but not in the UK. NBER Macroeconomics Annual, 18: 9-63.

Baum, C.F., Schaffer, M.E., Stillman, S. (2003). "Instrumental variables and GMM: estimation and testing." The Stata Journal 3 (1), 1-31.

Becker, G., (1964). Human Capital: A Theoretical and Empirical Analysis, With Special Reference to Education, New York: Columbia University Press.

Berman, E., Bound J., Griliches, Z., (1994). Changes in the demand for skilled labour within US manufacturing Industries: Evidence from the Annual Survey of Manufacturers. Quarterly Journal of Economics 109, 365-367.

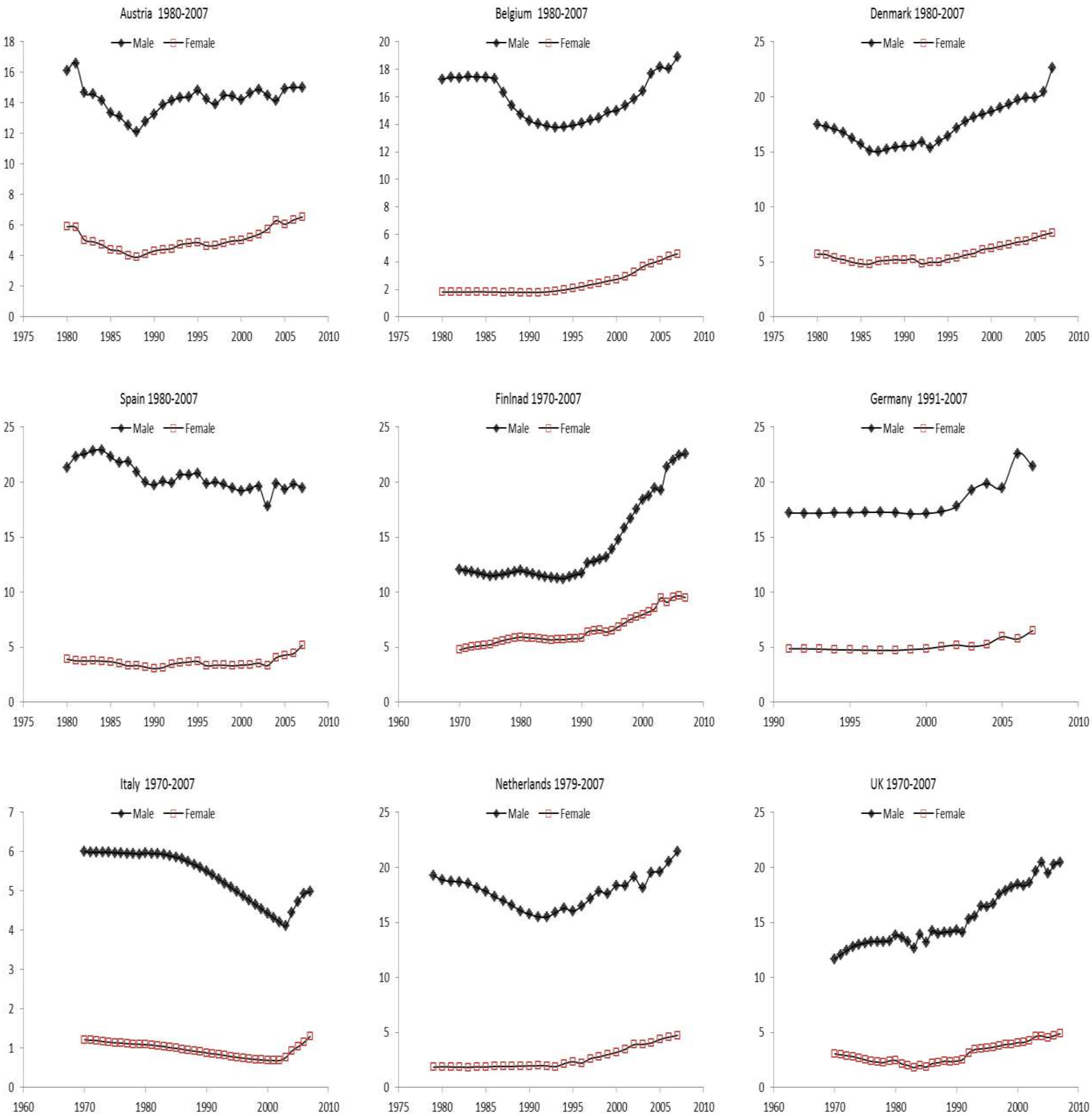
Blau, D. and Shvydko, T. (2011). Labor Market Rigidities and the Employment Behavior of Older workers. Industrial and Labor Relations Review, 64 (3), 464-484
Bogliacino, F., Piva, M., and Vivarelli, M. (2012). R&D and employment: An application of the LSDVC estimator using European microdata. Economics Letters, 116(1), 56-59.
Bonanno, G. (2016), ICT and R&D as inputs or efficiency determinants? Analysing Italian manufacturing firms (2007-2009), Eurasian Business Review, 6(3), 383-404.
Brouwer, E., Kleinknecht, A., Reijnen, J.O.N. (1993). Employment growth and innovation at the firm level: an empirical study. Journal of Evolutionary Economics 3, 153-159.
Brynjolfsson, E. and McAfee, A. (2014). The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies. New York: W.W. Norton.
Buttner T. (1999) The effect of unemployment, aggregate wages, and spatial contiguity on local wages: an investigation with German district level data, Papers in Regional Science 78, 47-67.
Card, D. and Lemieux, T. (2001), "Can Falling Supply Explain the Rising Return to College for Younger Men?" Quarterly Journal of Economics 705-46
Carmichael, F. and Ercolani, M.G. (2014). "Age-training gaps in the European Union." Ageing & Society 34, 129-156.
Caroli, E. and van Reenen, J. (2001). Skill-biased organisational change? Evidence from a panel British and French establishments. Quarterly Journal of Economics 116(4), 1449-1492.
Caselli, F., (1999). "Technological revolutions." American Economic Review, 89, 78-102.
Caselli, F., and W. J. Coleman, (2006). The world technology frontier. American Economic Review, 96(3), 499-522.
Chun, H., (2003). Information technology and the demand for educated workers: Disentangling the impacts of adoption versus use. The Review of Economics and Statistics 85, 1-8.
Ciriaci, D., Moncada-Paternò-Castello, P., and Voigt, P. (2016). Innovation and job creation: A sustainable relation? Eurasian Business Review, 6, 189-213.
Conti, M. and Sulis, G. (2016). Human capital, employment protection and growth in Europe. Journal of Comparative Economics 44(2), 213-230.
Daveri, F. and Maliranta, M. (2007), Age, seniority and labour costs: lessons from the Finnish IT revolution, Economic Policy, 117-175.
Dustmann, C., Ludsteck, J., and Schoberg, U. (2009). Revisiting the German Wage Structure.? Quarterly Journal of Economics 124 (2), 843-81.
Evangelista, R., Vezzani, A. (2012). The impact of technological and organizational innovations on employment in European firms. Industrial and Corporate Change, 21, 871-899.
Fraumeni, B.M. (1997), The Measurement of Depreciation in the U.S. National Income and Product Accounts, Survey of Current Business, Available at https://www.bea.gov/scb/account_articles/national/0797fr/maintext.htm
Frey, C.B., and Osborne, M.A. (2013). The future of employment: how susceptible are jobs to computerisation? Oxford University Working Paper, September 17, Oxford.
Garnero, A., Stephan, K. and Rycx, F. (2014), Minimum wage systems and earnings inequalities: Does institutional diversity Matter? European Journal of Industrial Relations, 1-16.
Goos, M, and Manning, A. (2007). Lousy and Lovely Jobs: The Rising Polarization of Work in Britain. Review of Economics and Statistics 89 (1): 118–33.
Goos, M., Manning, A., Salomons, A. (2014). Explaining job polarization: Routine-biased technological change and offshoring, The American Economic Review, 104, 2509-2526.
Goldin, C., Katz, L.F., (1998). The origins of technology-skill complementarity. Quarterly Journal of Economics, 113, 693–732.

Goux, D. and Maurin, E., (2000). The decline in demand for unskilled labor; an empirical analysis method and its application to France. Review of Economics and Statistics 82, 596-607.
Greenhalgh, C., Longland, M., Bosworth, D., (2001). Technological activity and employment in a panel of UK firms. Scottish Journal of Political Economy 48, 260–282.
Hall, B.H., Lotti, F., Mairesse, J. (2008). Employment, innovation, and productivity: evidence from Italian microdata. Industrial and Corporate Change 17, 813–839.
Hamilton J. (1994) Time Series Analysis. Princeton University Press, Princeton, NJ.
Harrison, R., Jaumandreu, J., Mairesse, J., Peters, B. (2014). Does innovation stimulate employment? A firm-level analysis using comparable micro-data from four European countries. International Journal of Industrial Organization, 35, 29-43.
Hayashi, F. (2000). Econometrics. Princeton, NJ: Princeton University Press.
Heckman, J., Stixrud, J., Urzua, S., 2006. The effects of cognitive and noncognitive abilities on labor market outcomes and social behaviour. Journal of Labor Economics 24 (3), 411–482.
Heywood, J and Siebert, S.W. (2009) Understanding the Labor Market for Older Workers: A Survey. IZA DP No. 4033.
Hurd, M. (1996). "The Effect of Labor Market Rigidities on the Labor Force Behavior of Older Workers", in D Wise (ed.), Advances in the Economics of Aging. Chicago: The University of Chicago Press.
Iversen, T. (1999). Contested Economic Institutions. The politics of macroeconomics and wage bargaining in advanced democracies. Cambridge, Mass., Cambridge University Press.
Jansen, G. (2014). Effects of Union Organization on Strike Incidence in EU Companies. Industrial and Labor Relations Review, 67(1), P60-85
Jorgenson, D.W., Landefeld, J.S., and Nordhaus, W.D. (eds) (2006). *A New Architecture for the U.S. National Accounts*, NBER Studies in Income and Wealth, Volume 66, The University of Chicago Press.
Kahn, J., Lim, J., (1998), Skill labour augmenting technical progress in U.S. manufacturing, Quarterly Journal of Economics 113, 1281–1308.
Kawaguchi, D. and Mori, Y. (2014), Winning the race against technology, Bank of Japan Working Paper No.14-E-5, Bank of Japan, Tokyo 103-0021, Japan.
Kristal, T. and Cohen, Y. (2016), "The causes of rising wage inequality: The race between institutions and technology." Socio-Economic Review, 1-26.
Kenworthy, L. (2001). "Wage-Setting Institutions: A survey and assessment." World Politics 54, 57-98.
Lachenmaier, S. and Rottmann, H. (2011), Effects of innovation on employment: A dynamic panel analysis. International Journal of Industrial Organization, 29, 210-220.
Lewis, E., (2011) "Immigration, Skill Mix, and Capital Skill Complementarity," Quarterly Journal of Economics 126 (2), 1029-1069
Machin, S., Van Reenen, J. (1998). "Technology and changes in skill structure: evidence from seven OECD countries." Quarterly Journal of Economics 113, 1215-1244.
Mallick, S.K., and Sousa, R.M. (2017) The Skill Premium Effect of Technological Change: New Evidence from the US Manufacturing Sector, International Labour Review, forthcoming.
Marouani, M.A. and Nilsson, B. (2016), "The labor market effects of skill-biased technological change in Malaysia." Economic Modelling 57, 55-75.
Mitra, A., Jha, A. (2015). Innovation and employment: A firm level study of Indian industries. Eurasian Business Review, 5, 45-71.
Messinis, G., and Ahmed, A.D. (2013). Cognitive skills, innovation and technology diffusion. Economic Modelling, 30(1), 565-578.

Michaels, G., Natraj, A. and Van Reenen, J. (2014). Has ICT Polarized Skill Demand? Evidence from Eleven Countries over Twenty-Five Years. Review of Economics and Statistics 96(1), 60-77.
Mincer, J. (1974). Schooling, Experience and Earnings, New York: National Bureau of Economic Research.
Mitchell, M. F., 2005. Specialization and the skill premium in the 20th Century. International Economic Review, 46(3), 935-955.
O'Mahony, M. and Peng, F. (2009). "Skill bias, age and organizational change," MPRA Paper 38767.
O'Mahony, M., Robinson, C. and Vecchi, M. (2008). The Impact of ICT on the Demand for Skilled Labour: A Cross-Country Comparison, Labour Economics, 15(6), 1435-1450.
O'Mahony, M. and Timmer, M.P. (2009). Output, Input and Productivity Measures at the Industry Level: the EU KLEMS Database. The Economic Journal 119 (June), F374-F403.
O'Mahony, M. and Van Ark, B. (2003). Eds., EU Productivity and Competitiveness – An Industry Perspective: Can Europe resume the Catching-up Process, European Commission Publication.
Pianta, M., 2005. Innovation and employment. In J. Fagerberg, D. Mowery and R.R. Nelson (eds), Handbook of Innovation. Oxford: Oxford University Press, 568-598.
Piva, M., Vivarelli, M., 2005. Innovation and employment: evidence from Italian microdata. Journal of Economics 86, 65-83.
Peng, F., and Kang, L. (2013). Labor Market Institutions and Skill Premiums: An Empirical Analysis on the UK, 1972-2002, Journal of Economic Issues, 47(4), 959-982.
Peng, F. and Siebert, W.S. (2008). Real Wage Cyclicality in Italy. Labour 22(4), 569-591.
Pierrard, O., and Sneessen, H. (2003). Low-skilled unemployment, biased technological shocks and job competition. IZA Discussion Paper 784, Institute for the Study of Labour. Available at http://ssrn.com/abstract=412490
Pierre, G., and Scarpetta, S. (2006). Employment protection: do firms' perceptions match with legislation? Economics Letters 90(3), 328-334.
Piore, M.J. (1979). Birds of Passage. Cambridge, UK: Cambridge University Press.
Ruiz-Arranz, M. (2004). Wage inequality in the US: capital-skill complementarity vs skill-biased technical change. IMF mimeo.
Stiroh, K.J., (2002). Information technology and the U.S. productivity revival: what do the industry data say? American Economic Review 92, 1559-1576.
Schone, P. (2009). New technologies, new work practices and the age structure of the Workers, Journal of Population Economics 22(3), 803-826.
Smolny, W. (1998). Innovations, prices and employment: a theoretical model and an empirical application for West German manufacturing firms. Journal of Industrial Economics 46, 359-381.
Spitz-Oener, A. (2006). Technical Change, Job Tasks, and Rising Educational Demands: Looking Outside the Wage Structure. Journal of Labor Economics 24 (2), 235-70.
Stock, J.H., and Watson, M. (2014). Introduction to Econometrics. 3rd edition. Boston, MA: Addison- Wesley
Timmer, M., Moergastel, T. V., Stuivenwold, E., O'Mahony, M., Kangasniemi, M., and Soo, A., et al. (2007a). EUKLEMS growth and productivity accounts version 1. 0 part 1: Methodology.http://www.euklems.net/data/EUKLEMS_Growth_and_Productivity_Accounts_Part_I_Methodology.pdf
Timmer, M., Moergastel, T. V., Stuivenwold, E., O'Mahony, M., Kangasniemi, M., and Soo, A., et al. (2007b). EUKLEMS growth and productivity accounts version 1. 0 part 2: Sources by country.
http://www.euklems.net/data/EUKLEMS_Growth_and_Productivity_Accounts_Part_II_S

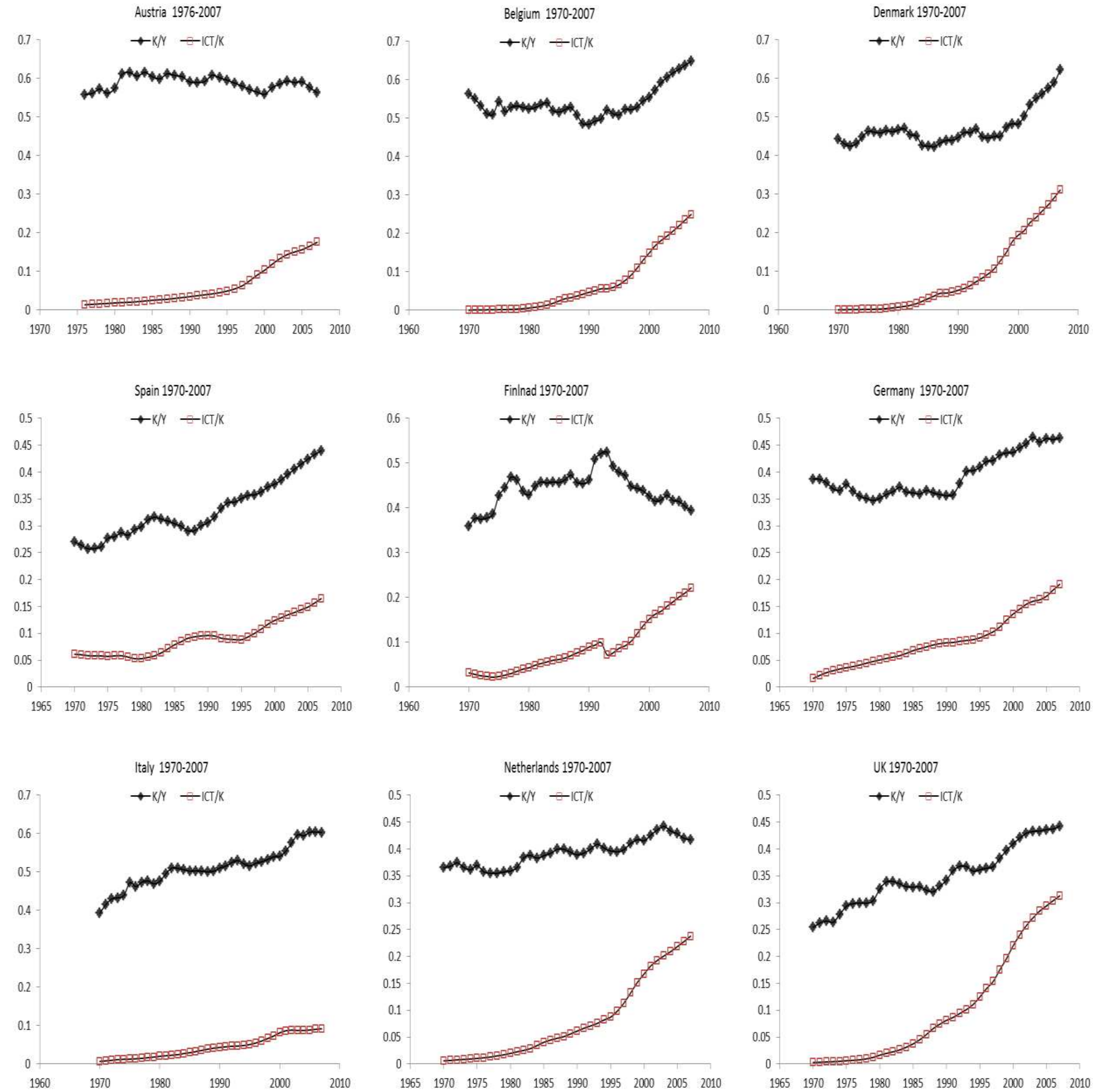
ources.pdf
Van Ark, B., O'Mahony, M. and Timmer, M.P. (2008). "The productivity gap between Europe and the United States." Journal of Economic Perspectives 22(1), 25-44.
Van Reenen, J., 1997. Employment and technological innovation: Evidence from U.K. manufacturing firms. Journal of Labour Economics, 15, 255-284.
Visser, J. (2015). ICTWSS Data base. Version 5.0. Amsterdam: Amsterdam Institute for Advanced Labour Studies AIAS. October 2015. Open access database (available at: www.uva-aias.net/208).
Vivarelli, M. (2014). Innovation, employment and skills in advanced and developing countries: A survey of economic literature. Journal of Economic Issues, 48, 123-154.
Vivarelli, M. and Pianta, M. (2000). The Employment Impact of Innovation: Evidence and Policy. London: Routledge.
Waldman, D. A. and Avolio, B. J. (1986). A meta-analysis of age differences in job performance, Journal of Psychology 71, 33-38
Wooden, M., van den Heuvel, A., Cully, M., and Curtain, R. (2001). "Barriers to training for older workers and possible policy solutions", Flinders National Institute of Labour Studies, University of South Australia. Available at http://www.dest.gov.au/archive/iae/documents/olderworkers/olderworekrsv4.pdf
Zhou, J. (2006). Reforming employment protection legislation in France. IMF Working Paper, no.108.

Figure 1: Wage bill shares for workers aged 50 and over (%) in 9 EU countries



Source: Author calculations based on EU-KLEMS data from 1970 to 2007.

Figure 2: Capital-Output and ICT Capital-Total Capital Ratios in 9 EU countries



Source: Author calculations based on EU-KLEMS data from 1970 to 2007.

Table 1a: Descriptive Statistics of Labour Compensation Variables (1970-2007)

Country	Males 50+				Females 50+			
	Obs	Labour compensation shares in %	Employment Shares in %	Relative wage	Obs	Labour compensation shares in %	Employment Shares in %	Relative wage
Austria***	308	14.3	11.9	1.2	295	5.0	4.7	1.1
Belgium***	308	15.9	13.8	1.2	295	2.4	3.9	0.7
Denmark***	308	17.4	16.2	1.1	243	5.8	7.1	0.8
Spain***	308	20.5	16.8	1.3	308	3.6	4.7	0.9
Finland*	418	14.2	11.0	1.4	418	6.6	7.4	0.9
Germany****	187	18.2	14.1	1.3	187	5.1	7.3	0.7
Italy*	418	5.4	9.0	0.7	418	1.0	2.3	0.6
Netherlands**	319	17.8	14.1	1.3	318	2.6	2.8	0.9
UK*	418	15.4	12.7	1.7	418	3.1	5.3	1.0

Table 1b: Descriptive Statistics of Capital Ratio, ICT Capital Ratio and Labour Market Institution Variables (1970-2007)

Country	Obs	Capital/ output in %	ICT/total capital in %	COORD	EXT	NMW	WAGE	PENSIONS	UD	CENT
Austria†	352	58.8	6.2	4.34	3.00	0.00	0.03	0.03	47.52	0.92
Belgium	407	53.7	6.3	4.34	3.00	1.74	0.03	0.13	50.74	0.47
Denmark	418	47.2	8.6	4.11	0.00	0.00	0.11	0.03	73.14	0.52
Spain	418	32.9	9.0	3.10	3.00	2.00	0.13	0.03	16.43	0.31
Finland	418	44.2	8.9	4.47	2.76	0.00	0.34	0.05	70.71	0.44
Germany	418	39.4	8.5	3.68	1.00	0.00	0.00	0.03	30.48	0.44
Italy	418	51.0	4.4	2.68	0.00	0.00	0.16	0.05	40.60	0.33
Netherlands	418	39.2	8.0	3.79	2.00	2.00	0.16	0.08	28.22	0.53
UK	418	34.8	10.3	1.66	0.29	1.08	0.11	0.00	40.12	0.18

Source: Author calculation based on EU-KLEMS and ICTWSS database. *Labour compensation data are only available from 1970-2007 for Finland, Italy and the UK; **1979-2007 for the Netherlands; ***1980-2007 for Austria, Belgium, Denmark and Spain; ****1991-2007 for Germany.

†Capital-output and ICT capital-total capital ratios are available for all countries, except Austria over the period 1970-2007. The time period for Austria is 1976-2007.

Table 2: Estimation of the wage share equations using aggregated data on 11 industries in 9 EU countries from1970 to 2007 (country, industry and year dummies are included in all equations)

Age 15-29 (young workers)						
Dependent variable: wage shares	Male			Female		
	High	Intermediate	Unskilled	High	Intermediate	Unskilled
	Degree	Below degree	None	Degree	Below degree	None
Ln(K/Y)	-0.349**	-1.280*	0.426	0.223	-0.918	-0.751
	(0.159)	(0.691)	(0.690)	(0.147)	(0.905)	(0.457)
Ln(ICT/K)	0.155**	-0.061	-1.767**	0.106**	-0.909**	-0.357
	(0.065)	(0.301)	(0.747)	(0.051)	(0.449)	(0.371)
R-squared	0.801	0.743	0.597	0.583	0.665	0.503
N	2973	2981	2974	2956	2976	2971
Age 30-49 (senior workers)						
Dependent variable: wage shares	Male			Female		
	High	Intermediate	Unskilled	High	Intermediate	Unskilled
	Degree	Below degree	None	Degree	Below degree	None
Ln(K/Y)	0.492	-0.034	1.734**	0.549**	-0.040	-0.767
	(0.511)	(1.226)	(0.676)	(0.257)	(0.905)	(0.584)
Ln(ICT/K)	0.545*	2.722***	-1.054**	0.313***	-0.359	0.005
	(0.313)	(0.807)	(0.417)	(0.104)	(0.591)	(0.309)
R-squared	0.799	0.854	0.811	0.684	0.778	0.637
N	2981	2981	2977	2976	2981	2981
Age 50+ (older workers)						
Dependent variable: wage shares	Male			Female		
	High	Intermediate	Unskilled	High	Intermediate	Unskilled
	Degree	Below degree	None	Degree	Below degree	None
Ln(K/Y)	0.233	-0.206	0.464	0.139**	-0.274	0.132
	(0.389)	(0.551)	(0.328)	(0.056)	(0.190)	(0.266)
Ln(ICT/K)	0.274*	0.102	-0.459**	0.069**	0.186**	0.224
	(0.153)	(0.512)	(0.192)	(0.027)	(0.078)	(0.137)
R-squared	0.682	0.719	0.837	0.454	0.738	0.661
N	2981	2981	2981	2891	2976	2980

Notes: Heteroskedasticity-robust standard errors are corrected for clustering of observations at the country*industry level and shown in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Table 3: GMM Estimation of wage equations using aggregated data (country, industry and year dummies are included in all equations)

Age 15-29 (young workers)						
Dependent variable: wage shares	Male			Female		
	High	Intermediate	Unskilled	High	Intermediate	Unskilled
	Degree	Below degree	None	Degree	Below degree	None
Ln(K/Y)	-0.286*	-0.667	0.100	0.231*	-0.480	-0.504
	(0.157)	(0.577)	(0.413)	(0.125)	(0.546)	(0.332)
Ln(ICT/K)	0.130**	0.018	-0.627**	0.087*	-0.997***	-0.258
	(0.065)	(0.274)	(0.296)	(0.048)	(0.336)	(0.224)
Hansen *J*- test	3.85	2.28	8.94	0.60	0.40	0.91
	(0.146)	(0.32)	(0.177)	(0.739)	(0.82)	(0.634)
C statistic	3.03	4.33	1.13	1.11	2.87	2.45
	(0.22)	(0.115)	(0.568)	(0.574)	(0.238)	(0.294)
R-squared	0.804	0.747	0.556	0.585	0.669	0.507
N	2907	2915	2842	2890	2910	2905
Age 30-49 (senior workers)						
Dependent variable: wage shares	Male			Female		
	High	Intermediate	Unskilled	High	Intermediate	Unskilled
	Degree	Below degree	None	Degree	Below degree	None
Ln(K/Y)	0.477	0.088	1.587**	0.495**	-0.039	0.245
	(0.440)	(1.105)	(0.654)	(0.245)	(0.800)	(0.408)
Ln(ICT/K)	0.396	2.543***	-0.989**	0.284***	-0.447	0.001
	(0.300)	(0.797)	(0.415)	(0.106)	(0.551)	(0.261)
Hansen *J*-test	1.64	1.54	1.72	1.25	0.05	9.02
	(0.441)	(0.463)	(0.422)	(0.536)	(0.976)	(0.173)
C statistic	2.35	2.27	1.95	2.24	0.33	1.25
	(0.309)	(0.321)	(0.378)	(0.326)	(0.847)	(0.536)
R-squared	0.807	0.853	0.810	0.689	0.780	0.588
N	2915	2915	2911	2910	2915	2849
Age 50+ (older workers)						
Dependent variable: wage shares	Male			Female		
	High	Intermediate	Unskilled	High	Intermediate	Unskilled
	Degree	Below degree	None	Degree	Below degree	None
Ln(K/Y)	-0.053	-0.226	0.201	0.133***	-0.238	0.291
	(0.214)	(0.484)	(0.314)	(0.049)	(0.162)	(0.185)
Ln(ICT/K)	0.133	0.208	-0.703***	0.061**	0.234**	0.121
	(0.132)	(0.282)	(0.171)	(0.028)	(0.094)	(0.118)
Hansen *J*-test	3.22	2.45	7.52	4.45	5.77	3.49
	(0.521)	(0.653)	(0.111)	(0.348)	(0.217)	(0.48)
C statistic	2.57	0.76	2	1.7	1.35	0.72
	(0.277)	(0.683)	(0.368)	(0.427)	(0.51)	(0.699)
R-squared	0.670	0.730	0.832	0.458	0.749	0.635
N	2882	2882	2882	2792	2844	2881

Notes: Heteroskedasticity-robust standard errors are corrected for clustering of observations at the country*industry level and shown in parentheses. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively. The orthogonality requirement is checked with an over-identification test (Hansen J statistic) in the presence of heteroskedasticity. The null hypothesis is that all instruments are valid. The C statistic is used to determine the exogeneity of the endogenous regressors. The null hypothesis is that the FE estimator is efficient and consistent. Failure to reject the null hypothesis implies that the FE estimates are to be preferred to the GMM IV estimates.

Table 4: Estimated Coefficient on ICT-Total Capital Ratio for Older Workers by Country (industry and year dummies are included in all equations)

Dependent variable: wage shares	Male			Female		
	High	Intermediate	Unskilled	High	Intermediate	Unskilled
	Degree	Below degree	None	Degree	Below degree	None
Austria	-0.286	0.767*	0.647**	0.069	-0.032	0.047
	(0.197)	(0.399)	(0.278)	(0.071)	(0.206)	(0.324)
R-squared	0.864	0.861	0.871	0.819	0.711	0.835
N	308	308	308	295	308	308
Belgium	-1.523***	-2.025	-0.135	-0.159	-0.807*	0.098
	(0.427)	(1.381)	(0.757)	(0.222)	(0.422)	(0.211)
R-squared	0.800	0.585	0.962	0.785	0.704	0.865
N	297	297	297	286	292	296
Denmark	-0.279	0.107	-1.166	-0.182***	-0.669*	0.312
	(0.290)	(0.773)	(0.779)	(0.053)	(0.359)	(0.395)
R-squared	0.925	0.841	0.825	0.844	0.883	0.834
N	308	308	308	243	308	308
Spain	0.394	0.346	0.774	-0.047	0.244*	0.039
	(0.728)	(0.392)	(1.012)	(0.081)	(0.121)	(0.850)
R-squared	0.905	0.886	0.956	0.746	0.754	0.953
N	308	308	308	308	308	308
Finland	-0.235	0.340	-0.093	-0.086	-0.010	0.060
	(0.258)	(0.412)	(0.181)	(0.175)	(0.100)	(0.158)
R-squared	0.882	0.738	0.931	0.678	0.833	0.876
N	418	418	418	418	418	418
Germany	-0.870**	-1.906*	1.055**	0.156	-0.477**	0.845**
	(0.329)	(0.923)	(0.340)	(0.088)	(0.211)	(0.283)
R-squared	0.959	0.893	0.924	0.908	0.984	0.930
N	187	187	187	187	187	187
Italy	-0.049	-0.238	0.067	-0.002	-0.079	-0.047
	(0.055)	(0.244)	(0.130)	(0.005)	(0.133)	(0.046)
R-squared	0.929	0.864	0.799	0.741	0.841	0.773
N	418	418	418	418	418	418
Netherlands	0.186	2.956	-0.123	0.074	0.334	-0.166*
	(0.238)	(1.978)	(0.491)	(0.111)	(0.373)	(0.088)
R-squared	0.920	0.639	0.887	0.625	0.900	0.815
N	319	319	319	318	319	319
UK	-0.530	0.733	0.086	-0.053	0.040	0.213
	(0.578)	(2.371)	(0.514)	(0.081)	(0.456)	(0.188)
R-squared	0.886	0.731	0.873	0.692	0.715	0.901
N	418	418	418	418	418	418

Notes: Heteroskedasticity-robust standard errors are corrected for clustering of observations at the industry level and shown in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Table 5: Estimates of the breakpoints for 9 EU countries

Dependent variable: wage shares	Male			Female			Average
	High Skilled	Intermediate Skilled	Unskilled	High Skilled	Intermediate Skilled	Unskilled	
	Degree	Below degree	None	Degree	Below degree	None	
Austria	1989*	1989***	1992***		1989***		1990
	4.16	***17.50***	***26.70***		***14.16***		
	2003**			2000***		1997***	2000
	5.48			***28.09***		***31.13***	
Belgium		1993***	1992***		1996***	1992***	1993
		45.69	***45.65***		***35.41***	***26.46***	
	2003***			2001***	2000***		2001
	26.63			***56.74***	***36.72***		
Denmark	1992*	1987***			1989***		1989
	4.42	***27.72***			***13.33***		
	2002***		2003***	2002***		2003***	2003
	8.62		***15.47***	***25.80***		***18.21***	
Spain	1994*		1984***				1989
	4.61		***16.77***				
		2003***		2003***	2003***	2002***	2003
		56.39		***27.01***	***78.69***	***6.16***	
Finland		1987***	1982**	1988***		1978***	1984
		128.14	***5.19***	***99.22***		***26.81***	
	1990***		1999***		1993***		1994
	81.76		***6.16***		***46.64***		
Germany	2002***	2003***	2004***	2002***	2004***	2004***	2003
	27.22	***17.13***	***10.46***	***42.23***	***43.07***	***44.74***	
Italy	1987***	1990***	1990***			1990***	1989
	11.07	***18.92***	***48.07***			***48.31***	
	2001***			2000***	2001***		2001
	26.06			***47.16***	***181.20***		
Netherlands	1992***	1994***	1995***	1997***	1998***	1994***	1995
	46.51	***59.50***	***272.36***	***50.91***	***101.22***	***36.28***	
UK	1991***	1986***	1983***	1995***	1987***	1991***	1989
	29.35	***74.80***	***48.32***	***49.71***	***267.33***	***26.22***	

Notes: The Quandt likelihood ratio (QLR test) or sup-Wald statistic is a modified version of the Chow test used to identify break dates. The estimated values of the test statistic are reported under the break year in bold and *italics*. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively. The critical values of QLR statistics with 15% trimming and three restrictions (break and its interactions with K/Y and ICT/K) are taken from Stock and Watson (2014).

Table 6: Estimated Coefficient on ICT-Total Capital Ratio for Older workers (50+) by country over time (industry and year dummies are included in all equations)

	Male			Female		
Dependent variable: wage shares	High Skilled Degree	Intermediate Skilled Below degree	Unskilled None	High Skilled Degree	Intermediate Skilled Below degree	Unskilled None
Austria	-0.127	0.589**	0.876*	0.109	0.009	-0.087
$\ln(ICT/K)_{80\text{-}90}$	(0.230)	(0.253)	(0.395)	(0.088)	(0.251)	(0.247)
	0.387	0.015	0.358	0.048	0.164	-0.124
$\ln(ICT/K)_{90\text{-}00}$	(0.408)	(0.225)	(0.307)	(0.047)	(0.202)	(0.136)
	0.401	-0.855**	0.774	0.015	0.081	-0.557*
$\ln(ICT/K)_{00\text{-}07}$	(0.237)	(0.279)	(0.531)	(0.079)	(0.349)	(0.281)
R-squared	0.873	0.881	0.890	0.832	0.714	0.855
N	308	308	308	295	308	308
Belgium	-1.530***	-1.180	-0.565	-0.210	-1.137***	0.027
$Ln(ICT/K)_{80\text{-}93}$	(0.339)	(0.986)	(0.891)	(0.121)	(0.315)	(0.179)
	0.036	-0.287	0.703**	0.114***	0.321**	0.075
$Ln(ICT/K)_{93\text{-}01}$	(0.212)	(0.294)	(0.278)	(0.029)	(0.108)	(0.103)
	-0.515	-2.069	0.413	0.346**	0.685*	0.166
$Ln(ICT/K)_{01\text{-}07}$	(0.314)	(1.791)	(0.473)	(0.139)	(0.388)	(0.210)
R-squared	0.818	0.623	0.967	0.859	0.751	0.867
N	297	297	297	286	292	296
Denmark	-0.041	0.041	-0.634	-0.096**	-0.399	0.287
$Ln(ICT/K)_{80\text{-}89}$	(0.178)	(1.043)	(0.548)	(0.039)	(0.573)	(0.388)
	0.266**	-0.444	1.155	0.043	0.488	-0.122
$Ln(ICT/K)_{89\text{-}03}$	(0.102)	(0.913)	(0.641)	(0.037)	(0.328)	(0.113)
	0.719**	-0.406	1.328	0.257***	1.037	0.073
$Ln(ICT/K)_{03\text{-}07}$	(0.254)	(1.200)	(1.303)	(0.044)	(0.800)	(0.461)
R-squared	0.944	0.860	0.856	0.889	0.902	0.846
N	308	308	308	243	308	308
Spain	0.432	0.362	1.013	-0.032	0.287**	0.102
$Ln(ICT/K)_{80\text{-}89}$	(0.729)	(0.397)	(1.060)	(0.078)	(0.126)	(0.750)
	0.201	0.128	-0.350	-0.010	0.013	0.293
$Ln(ICT/K)_{89\text{-}03}$	(0.275)	(0.130)	(0.409)	(0.030)	(0.048)	(0.171)
	0.890	0.358*	0.354	0.134	0.297	0.745**
$Ln(ICT/K)_{03\text{-}07}$	(0.654)	(0.167)	(1.000)	(0.133)	(0.238)	(0.299)
R-squared	0.912	0.888	0.957	0.796	0.793	0.959
N	308	308	308	308	308	308
Finland	-0.288	-0.109	0.001	0.143	0.196*	0.082
$Ln(ICT/K)_{70\text{-}84}$	(0.306)	(0.203)	(0.199)	(0.145)	(0.104)	(0.133)
	-0.310*	-0.316	0.614**	0.364**	0.176	0.071
$Ln(ICT/K)_{84\text{-}94}$	(0.168)	(0.186)	(0.264)	(0.143)	(0.100)	(0.385)
	-0.082	-2.755***	0.777	1.958**	0.918***	0.022
$Ln(ICT/K)_{94\text{-}07}$	(0.503)	(0.583)	(0.653)	(0.639)	(0.250)	(0.841)
R-squared	0.883	0.846	0.942	0.838	0.878	0.875
N	418	418	418	418	418	418
Germany	-0.889***	-1.859**	1.076***	0.144**	-0.509**	0.849**
$Ln(ICT/K)_{91\text{-}03}$	(0.266)	(0.683)	(0.319)	(0.057)	(0.196)	(0.282)
	0.381*	0.907	-0.327*	-0.086	-0.003	0.220
$Ln(ICT/K)_{03\text{-}07}$	(0.192)	(0.712)	(0.156)	(0.051)	(0.093)	(0.140)
R-squared	0.963	0.908	0.929	0.931	0.985	0.935
N	187	187	187	187	187	187
Italy	-0.049	-0.271	0.141**	-0.003	-0.107	-0.040
$Ln(ICT/K)_{70\text{-}89}$	(0.056)	(0.276)	(0.046)	(0.006)	(0.121)	(0.040)

$Ln(ICT/K)_{89-01}$	0.011	-0.084	0.337***	0.002	-0.010	0.052
	(0.019)	(0.126)	(0.079)	(0.003)	(0.053)	(0.031)
$Ln(ICT/K)_{01-07}$	0.042	-0.064	0.612***	-0.005	0.009	0.094
	(0.043)	(0.366)	(0.113)	(0.006)	(0.112)	(0.056)
R-squared	0.933	0.879	0.932	0.774	0.893	0.802
N	418	418	418	418	418	418
Netherlands	0.307	2.091	-0.134	0.064	0.317	-0.164*
$Ln(ICT/K)_{79-95}$	(0.278)	(1.341)	(0.428)	(0.107)	(0.305)	(0.084)
$Ln(ICT/K)_{95-07}$	0.293	-2.411*	0.047	-0.005	0.046	-0.006
	(0.261)	(1.101)	(0.204)	(0.115)	(0.273)	(0.044)
R-squared	0.921	0.700	0.900	0.645	0.916	0.822
N	319	319	319	318	319	319
UK	-0.536	0.693	0.147	-0.048	0.044	0.224
$Ln(ICT/K)_{70-89}$	(0.569)	(2.198)	(0.517)	(0.073)	(0.507)	(0.164)
$Ln(ICT/K)_{89-07}$	0.326	-1.582	-0.370	0.313**	0.630	-0.597*
	(0.401)	(1.225)	(0.656)	(0.124)	(0.631)	(0.272)
R-squared	0.887	0.741	0.882	0.787	0.735	0.921
N	418	418	418	418	418	418

Notes: Heteroskedasticity-robust standard errors are corrected for clustering of observations at the industry level and shown in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively. Subscripts like 89-07 denote the estimated coefficient using 1989 to 2007 data.

Table 7: Estimation of the wage share equation (4) using aggregated data from 11 industries in 9 EU countries from1970 to 2007 (country, industry and year dummies are included in all equations)

Age 50+ (Older Workers)						
Dependent variable: wage shares	Male			Female		
	High	Intermediate	Unskilled	High	Intermediate	Unskilled
	Degree	NVQ 1-4	None	Degree	NVQ 1-4	None
Ln(K/Y)	0.097	-0.442	0.439	0.132**	-0.33	0.164
	(0.340)	(0.526)	(0.334)	(0.056)	(0.199)	(0.260)
Ln(ICT/K)	0.102	-0.245	-0.557***	0.064**	0.100	0.253*
	(0.161)	(0.472)	(0.193)	(0.030)	(0.092)	(0.149)
COORD	-0.084*	-0.012	0.032	0.001	0.001	0.021
	(0.043)	(0.079)	(0.076)	(0.011)	(0.030)	(0.022)
EXT	-1.592***	0.059	-0.564**	-0.377***	-0.050	0.251**
	(0.227)	(0.911)	(0.225)	(0.119)	(0.147)	(0.099)
NMW	0.301***	0.739***	-0.263***	0.064*	0.232***	-0.198***
	(0.096)	(0.203)	(0.081)	(0.038)	(0.073)	(0.045)
WAGE	0.282***	0.705***	0.092	0.109***	0.248***	-0.030
	(0.051)	(0.148)	(0.127)	(0.022)	(0.040)	(0.028)
PENSIONS	-0.315***	-0.752***	0.340***	-0.100***	-0.124**	0.008
	(0.060)	(0.128)	(0.084)	(0.027)	(0.054)	(0.031)
UD	0.018	-0.035	-0.118***	0.016**	-0.000	-0.020**
	(0.022)	(0.028)	(0.025)	(0.007)	(0.012)	(0.009)
CENT	-0.841	-8.482***	0.887	0.375	-2.218***	0.409
	(0.900)	(1.939)	(1.085)	(0.299)	(0.827)	(0.577)
R-squared	0.711	0.733	0.846	0.483	0.747	0.666
N	2970	2970	2970	2880	2965	2969

Notes: Heteroskedasticity-robust standard errors are corrected for clustering of observations at the country*industry level and shown in parentheses. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively.

Table 8: Estimation of the relative wage equation (6) using aggregated data from 11 industries in 9 EU countries from1970 to 2007 (country, industry and year dummies are included in all equations)

Age 50+ (Older Workers)						
Dependent variable: relative wages	Male			Female		
	High	Intermediate	Unskilled	High	Intermediate	Unskilled
	Degree	NVQ 1-4	None	Degree	NVQ 1-4	None
Ln(K/Y)	-0.025	0.013	0.335**	-0.083	0.014	0.127
	(0.085)	(0.064)	(0.162)	(0.078)	(0.041)	(0.110)
Ln(ICT/K)	-0.000	0.025	0.091*	0.039	0.033	0.073*
	(0.053)	(0.032)	(0.058)	(0.052)	(0.023)	(0.039)
COORD	0.020	0.056***	0.059	-0.035*	0.009	0.036
	(0.025)	(0.020)	(0.062)	(0.019)	(0.016)	(0.051)
EXT	-0.576***	0.231***	0.053	-0.303***	0.028	-0.035
	(0.110)	(0.064)	(0.089)	(0.061)	(0.064)	(0.070)
NMW	0.211	-0.432***	-0.721***	0.303***	-0.180**	-0.488***
	(0.175)	(0.078)	(0.254)	(0.039)	(0.070)	(0.112)
WAGE	-0.158***	0.041	0.097*	-0.039	0.045	0.032
	(0.035)	(0.035)	(0.053)	(0.032)	(0.033)	(0.041)
PENSIONS	0.041	0.040	-0.123*	-0.040	0.061*	-0.050
	(0.035)	(0.025)	(0.062)	(0.037)	(0.035)	(0.043)
UD	0.013**	0.000	-0.010*	0.013***	0.011**	0.000
	(0.006)	(0.003)	(0.006)	(0.003)	(0.004)	(0.005)
CENT	0.050	0.185	1.428	0.441	-0.585	-1.061
	(0.689)	(0.304)	(0.912)	(0.508)	(0.605)	(1.017)
R-squared	0.697	0.678	0.327	0.622	0.390	0.230
N	2695	2695	2694	2603	2690	2694

Notes: Heteroskedasticity-robust standard errors are corrected for clustering of observations at the country*industry level and shown in parentheses. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively.

Table 9: Estimation of the employment share equation (7) using aggregated data from 11 industries in 9 EU countries from1970 to 2007 (country, industry and year dummies are included in all equations)

Age 50+ (Older Workers)						
Dependent variable: employment share	Male			Female		
	High	Intermediate	Unskilled	High	Intermediate	Unskilled
	Degree	NVQ 1-4	None	Degree	NVQ 1-4	None
Ln(K/Y)	-0.059	-0.298	0.457	0.214***	-0.402	-0.232
	(0.155)	(0.426)	(0.410)	(0.066)	(0.268)	(0.400)
Ln(ICT/K)	-0.039	-0.040	-0.690**	0.091***	-0.015	0.246
	(0.085)	(0.195)	(0.280)	(0.026)	(0.132)	(0.241)
COORD	-0.154***	-0.094	0.067	-0.045***	-0.035	0.004
	(0.047)	(0.083)	(0.099)	(0.014)	(0.031)	(0.074)
EXT	-0.329	-2.552***	-0.584	-0.703***	-0.660**	0.824***
	(0.224)	(0.526)	(0.512)	(0.200)	(0.252)	(0.199)
NMW	-0.232	1.608***	0.228	-0.066	0.088	0.740***
	(0.183)	(0.288)	(0.293)	(0.070)	(0.116)	(0.220)
WAGE	0.427***	0.251	-0.940**	0.118***	0.192**	-0.276*
	(0.065)	(0.219)	(0.390)	(0.023)	(0.091)	(0.153)
PENSIONS	-0.348***	-0.418***	1.426***	-0.086***	-0.106	0.420***
	(0.074)	(0.147)	(0.229)	(0.027)	(0.070)	(0.119)
UD	0.011	0.063***	-0.217***	0.014**	0.026**	-0.043*
	(0.013)	(0.016)	(0.045)	(0.006)	(0.011)	(0.023)
CENT	1.832	-4.999**	-10.615**	-0.366	-2.604*	-1.346
	(1.480)	(2.214)	(4.352)	(0.494)	(1.408)	(1.939)
R-squared	0.767	0.695	0.715	0.634	0.791	0.553
N	2695	2695	2694	2641	2694	2694

Notes: Heteroskedasticity-robust standard errors are corrected for clustering of observations at the country*industry level and shown in parentheses. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively.

Table 10: Estimation of the wage share equation (8) using dynamic specification (country, industry and year dummies are included in all equations)

Age 50+ (Older Workers)						
Dependent variable: wage share changes	Male			Female		
	High	Intermediate	Unskilled	High	Intermediate	Unskilled
	Degree	NVQ 1-4	None	Degree	NVQ 1-4	None
Lagged Wage shares	-0.066***	-0.047***	-0.029***	0.027**	-0.037***	-0.041***
	(0.013)	(0.010)	(0.006)	(0.011)	(0.009)	(0.004)
Ln(K/Y)	0.003	-0.021	0.048**	0.006	0.035**	0.019*
	(0.023)	(0.037)	(0.019)	(0.005)	(0.014)	(0.011)
Ln(ICT/K)	0.002	-0.004	-0.002	0.005**	0.006	0.006
	(0.018)	(0.025)	(0.010)	(0.002)	(0.005)	(0.004)
COORD	-0.034**	0.020	-0.016	0.004	0.003	-0.004
	(0.013)	(0.027)	(0.021)	(0.004)	(0.006)	(0.006)
EXT	-0.269***	-0.046	0.164***	-0.020	-0.039	0.075***
	(0.059)	(0.128)	(0.056)	(0.013)	(0.038)	(0.028)
NMW	0.058***	-0.215***	0.016	0.005	-0.064***	-0.039***
	(0.019)	(0.035)	(0.022)	(0.007)	(0.016)	(0.011)
WAGE	0.045*	0.074	0.064	-0.002	-0.013	0.015
	(0.023)	(0.057)	(0.040)	(0.006)	(0.015)	(0.014)
PENSIONS	-0.029	-0.104	-0.063*	-0.013	-0.013	-0.036*
	(0.036)	(0.075)	(0.037)	(0.011)	(0.029)	(0.018)
UD	0.007***	-0.011	0.000	0.001**	-0.001	-0.000
	(0.002)	(0.008)	(0.004)	(0.001)	(0.001)	(0.001)
CENT	0.389**	-0.165	-0.526**	0.024	-0.295*	-0.186*
	(0.150)	(0.376)	(0.254)	(0.033)	(0.152)	(0.110)
R-squared	0.075	0.157	0.102	0.071	0.108	0.079
N	2871	2871	2871	2774	2866	2869

Notes: Heteroskedasticity-robust standard errors are corrected for clustering of observations at the country*industry level and shown in parentheses. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively.